GENDER DISCRIMINATION AND ECONOMIC OUTCOMES IN CHILE

Final Report

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Presentation

The study "Gender Discrimination and Economic Outcomes in Chile" is an ambitious attempt at providing systematic evidence for an area of great interest.

This project is comprised of three studies that the Centro de Microdatos of the Department of Economics of the Universidad de Chile is developing in parallel. This final report presents the final papers in its three components.

Firstly, the chapter "An Experimental Study about Labor Market Discrimination: Gender, Social Class and Neighborhood" is presented. This paper examines whether there are differences in the response rate for curriculum vitae sent in response to job vacancies published in the main newspaper of Chile, both for gender and socioeconomic characteristics. In the version of the article presented, results are obtained for 3,500 CVs sent.

Secondly, the study "Is there labor market discrimination among professionals in Chile? Lawyers, Doctors and Business-people" is presented. This paper is done based on a survey colleted specially for these effects. It is the first database of professionals in Chile containing data on non-cognitive abilities, real labor market history, social and family background and others. The aim is to investigate whether taking into account many variables that in generally are unobservable we still have differences in wages to only to gender.

Finally, the third chapter of this project includes is called "Ability, Schooling Choices and Gender Labor Market Discrimination: Evidence for Chile". This paper studies the importance of schooling decisions and abilities in explaining gender gaps in wages. In the analysis we use a rich data set for Chile (the Social Protection Survey). This data set contains information not only on labor market outcomes but also on schooling attainment and schooling performance. We introduce an empirical model in which agents make schooling and labor market choices based on this unobserved ability (in addition to observables). We use schooling performance to identify the distribution of unobserved abilities in the population.

Acknowledgements

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Chapter 1

"An Experimental Study about Labor Market Discrimination: Gender, Social Class and Neighborhood"

Abstract

The objective of this chapter is to study the Chilean labor market and determine the presence or absence of gender discrimination. In order to break past the limitations of earlier works, an experimental design is used, the first of its kind in Chile. This study also allows socioeconomic discrimination associated to names and places of residence in the Chilean labor market to be tackled.

The study consists of sending fictitious Curriculum Vitae for real job vacancies published weekly in the "El Mercurio" newspaper of Santiago. A range of strictly equivalent CVs in terms of qualifications and employment experience of applicants are sent out, only varying in gender, name and surname, and place of residence. The study allows differences in call response rates to be measured for the various demographic groups. In the version of the article presented, results are obtained for 6,300 CVs sent.

Our results show no significant differences in callback rates across groups, in contrast with what is found in other international studies.

1 Introduction

Gender and social discrimination in the labor market are some of the key issues in the discussion on public policies in Latin America. However, empirical evidence and academic research on the matter have been rather scarce until now. This is also the case in Chile.

No matter how much has been done to study labor market discrimination, either racial, ethnic or gender, the issue of detection is still unsettled. In the usual regression analyses there are several problems of unobservable variables that clearly bias the results (Altonji and Blank, 1999; Neal and Johnson, 1996) and, on the other hand, experimental studies have been under discussion for not correctly measuring discrimination (Heckman and Siegelman, 1993; Heckman, 1998).

In Chile, despite the fact that the average years of schooling of Chilean female workers are not statistically different from those of male workers, average wages of male workers are 25% higher[1]. In fact, previous studies[2] suggest that gender discrimination is a factor in determining wages in the Chilean labor market. Estimates of the Blinder-Oaxaca decomposition give "residual discrimination" a significant participation in the total wage gap[3]. The evidence also shows stable and systematic differences in the returns to education and to experience by gender along the conditional wage distribution. Additionally, it has been shown that "residual discrimination" is higher for women with more education and experience.

Furthermore, Chilean female labor force participation is particularly low, 38.1% compared to 44.7% in Latin America[4]. This is even lower for married women and in fact, higher participation is found in separated or divorced women (Bravo, 2005). This latter fact may be interpreted as evidence of female preferences for non-market activities[5].

However, this "residual discrimination" is only a measure of how much of the wage gap is due to unobservable factors. Therefore, these measures of discrimination are biased due to the lack of relevant controls. A recent study on discrimination by social class in Chile (Núñez

[1] Own calculations using CASEN 2003. Once you correct for human capital differences and occupational choice this gap falls to 19% approximately.
[2] Previous studies for Chile are Bravo (2005); Montenegro (1998); Montenegro and Paredes (1999) and Paredes and Riveros (1994).
[3] Bravo (2005) shows that taking all employed workers and after controlling for years of schooling and occupation, the wage gap was 13.5% in 2000. Using the Blinder-Oaxaca decomposition he concludes that most of this difference was due to "residual discrimination".
[4] Source: International Labor Organization (ILO).
[5] Contreras and Plaza (2004) also found that there are cultural factors, such as sexism, that significantly influence female labor force participation in Chile.

and Gutiérrez, 2004) uses a dataset which reduces the role of unobserved heterogeneity across individuals, but it has several limitations[6]. Furthermore, there are no attempts at studying discrimination using neither audit studies nor natural experiments.

The objective of this chapter is to study the Chilean labor market and determine the presence or absence of gender discrimination. In order to break past the limitations of earlier works, an experimental design is used, the first of its kind in Chile. This study also allows socioeconomic discrimination associated to names and places of residence in the Chilean labor market to be tackled.

The study consists of sending fictitious Curriculum Vitae for real job vacancies published weekly in the "El Mercurio" newspaper of Santiago. A range of strictly equivalent CVs in terms of qualifications and employment experience of applicants are sent out, only varying in gender, name and surname, and place of residence. The study allows differences in call response rates to be measured for the various demographic groups. In the version of the article presented, results are obtained for 6,300 CVs sent.

The following section contains a review of the relevant literature for this study. Meanwhile, Section III contains all the methodological information associated to the implementation of the experiment, which began to be applied in the last week of March 2006. Lastly, Section IV contains the preliminary results recorded to date.

2 Literature Review

Labor market discrimination is said to arise when two identically productive workers are treated differently on the grounds of the worker's race or gender, when race or gender do not in themselves have an effect on productivity (Altonji and Blank, 1999; Heckman, 1998).

However, there are never identical individuals. There are several unobservable factors that determine individual performance in the labor market (see literature review in chapter 2).

The empirical literature attempts to face these problems by two alternative methodologies: regression analysis and field experiments[7].

The regression analysis is focused on analyzing the Blinder-Oaxaca decomposition (Oaxaca, 1973; Blinder, 1973) to determine how much of the wage differential between groups of workers, by race or gender, is unexplained. This unexplained part is called discrimination.

[6] See Section II for a discussion.

[7] See Altonji and Blank (1999) and Blank, Dabady and Citro (2004) for complete surveys on the econometric problems involving detecting discrimination in the labor market using regression analysis and field experiments.

Developments in Chile have been centered on regression analysis applied to the gender gap. See Paredes and Riveros (1993), Montenegro (1999) and Montenegro and Paredes (1999) as an example. The conclusions from these studies are very limited. They lack several control variables, related to cognitive and non-cognitive abilities and school and family environments. In addition, preferences over non-market activities and experience of Chilean female workers could prove to be a very important unobservable factor. More recently, Núñez and Gutiérrez (2004) study social class discrimination in Chile under the traditional Blinder-Oaxaca decomposition. They use a dataset that allows them to reduce the role of unobservable factors by limiting the population under study and having better measures of productivity (see more details on these references in chapter 2).

The above represent the traditional studies in this area. The present article is much more closely related to a different line of research on labor market discrimination: experimental studies[8]. These originated in Europe in the 1960s and 1970s, the ILO in the 1990s and recently experimental techniques have been published in leading economic journals (Bertrand and Mullainathan, 2004).

Experimental approaches can be divided into two types: audit studies and natural experiments. The latter ones take advantage of unexpected changes in policies or events (Levitt, 2004; Antonovics, Arcidiacono and Walsh, 2004, 2005; Goldin and Rouse, 2000, Newmark, Bank and Van Nort, 1996). In Chile, as far as we know, there are no studies using these kinds of variations.

There have been two procedures used to carry out audit studies. First, the personal approach strategy, which sends individuals to job interviews or does job applications over the telephone. Second, there is the strategy of sending written applications for real job vacancies.

The first procedure is the most subject to criticisms. It has been argued that it is impossible to ensure that false applicants are identical. Also, testers were sometimes warned that they were involved in a discrimination study and their behavior could bias the results.[9]

The first experiments that used written applications were unsolicited jobs-applications and posted to "potential employers"; these experiments tested preferential treatment in employer responses and not the hiring decision. Later came the ones that sent curriculum vitae to real solicitudes. Despite the fact that this latter technique overcomes the criticisms of the personal approaches and tests the hiring decision[10] it does not overcome a common problem of the audit studies raised by Heckman and Siegelman (1993) and Heckman (1998), which is that audits are crucially dependent on the distribution of unobserved characteristics for each

[8] Riach and Rich (2002, 2004) and Anderson, Fryer and Holt (2005) have a complete survey of these studies.
[9] See Heckman and Siegelman (1993).
[10] It really tests the calling back decision. We do not know what can happen next.

racial group and the audit standardization level. Thus, there may still be unobservable factors, which can be productivity-determining and not discrimination. Riach and Rich (2002) accepted this criticism but pointed out that it is not easy to imagine how firm internal attributes[11] could enhance productivity. They conclude that while Heckman and Siegelman (1993) do not explain what could be behind those gaps the argument has "not been proven".

The present study mainly follows the line of work developed by Bertrand and Mullainathan (2004). In their study, the authors measured the racial discrimination in the labor market, by means of the posting of fictitious curriculum vitae for job vacancies published in Boston and Chicago newspapers. Half of the CVs were randomly given Afro-American names and the other half received European names. Additionally, the effect of applicant qualification on the racial gap was measured; for this, the CVs were differentiated between High Qualifications and Low Qualifications.

The authors found that the curriculum vitae associated to White names received 50% more calls for interview than those with Afro-American names. They also found that whites were more affected by qualification level than blacks. Additionally, the authors found some evidence that employers were inferring social class based on the applicants' names.

3 Experiment Design

As already indicated, the experiment consists of the sending out of CVs of fictitious individuals for real job vacancies that appear weekly in the newspaper with the highest circulation in Chile.

Each week, the work team selects a total of 60 job vacancies from the "El Mercurio" newspaper of Santiago. A total of 8 CVs, 4 corresponding to men and 4 to women are sent out for each vacancy. The details of the experiment design are presented here below.

3.1 Definition of Demographic Cells

We defined eight relevant demographic cells which determined the categories being studied in the experiment. Thus, eight CVs -that are equivalent as regards employment productivity but differ in the variables in question- were sent out for each vacancy.

[11] Such as internal promotion or other.

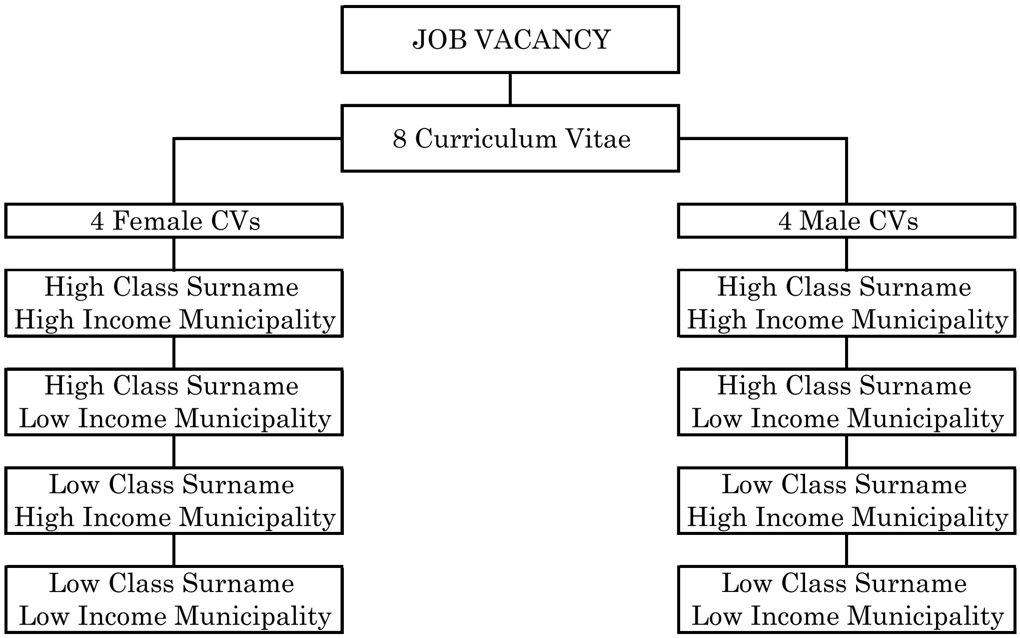
The cells were defined to serve the objectives of the study. Firstly, the study of discrimination by gender requires men and women to be separated. Additionally, socioeconomic discrimination is examined by means of two variables: surnames and municipalities of residence. In order to reduce the number of observations required in each case, these last variables were separated into two groups, the most extreme: socioeconomically rich and poor municipalities; and surnames associated to the Upper Classes and Lower Classes.

Since we have three dichotomous variables, the final number of demographic cells is 8 (2*2*2), as the following Table shows:

	Hombre		Mujer	
	Apellido Clase Alta	Apellido Clase Baja	Apellido Clase Alta	Apellido Clase Baja
Comuna Ingresos Altos				
Comuna Ingresos Bajos				

From the outset of the field work, in the last week of March 2006, each week approximately 60 job vacancies are chosen. Eight CVs are sent for each job vacancy, in other words, one for each demographic cell. So, each week 480 CVs are sent, 240 to men and 240 to women.

A group of names, surnames and municipalities are established to satisfy the requirements of each cell, with the names and municipalities chosen randomly for each vacancy.



3.2 Description of the source of job vacancies

The main source of job vacancies in Santiago is the "El Mercurio" newspaper, which publishes every Sunday around 150 job vacancies, with a repeat rate of around 30%. The ads are also available in the newspaper webpage, which facilitates access (see: http://empleos.elmercurio.com/buscador/destacados/listado_destacado.asp)

To prepare the field work, a prior study was carried out on this source. To this effect, in the month of January and the first three weeks of March 2006, all vacancies published were analyzed in order to design the future mailing strategy. In effect, it was possible to conclude from this study that it is necessary to prepare a CV bank based on three categories: professionals, technicians (skilled workers) and unskilled workers. Other markedly male or female categories were rejected and the approximate number of vacancies for each week was calculated.

3.3 Creation of CV Banks.

As indicated above, job vacancies are grouped into three categories: Professionals, Technicians and Unskilled workers. A person was assigned responsibility for each category, and is in charge of selecting the weekly vacancies, as well as the production, sending and supervision of the CVs sent.

Each person in charge (three in total) has a CV bank obtained from the www.laborum.com and www.infoempleo.cl websites. These are used as the base information for producing fictitious CVs and comply with the profile of the most competitive applicant for the vacancy selected.

Each set of 8 CVs is constructed so that its qualification levels and employment experience are equivalent, in order to ensure that the applicants are equally eligible for the job in question.

The central element in the training of the people in charge of this was to ensure that the 8 CVs sent for each vacancy had to be equivalent in terms of qualifications and human capital. To ensure this, the coordinators of the study were supported by a research assistant that supervised the work over the whole period and, especially, during the first weeks, until ensuring the desired results.

3.4 Classification of municipalities

In order to facilitate the field work, the study is concentrated in the Metropolitan Urban Region, which is divided into 34 municipalities.

To classify the municipalities in the two extreme segments, the socioeconomic classification of households based on the 2002 Census designed by Adimark was used. This institution classified from the CASEN 2003 Survey. Using this, it classifies the proportion of the population by socioeconomic level in each municipality. The groups are ordered from higher to lower level, ABC1, C2, C3, D and E.

For high income municipalities, 5 of the 6 with the highest proportion of the population in segment ABC1 were chosen (the sixth was excluded because it is a municipality that also had a higher proportion than the rest in segment D and E). On the other hand, for the low income group municipalities, the 15 municipalities associated to a lower proportion of the population in segment ABC1 and a greater proportion in the segments D and E were chosen. In order to more clearly examine the impact of the municipality of origin, all other municipalities of intermediate socioeconomic groups were left out.

The final list of the municipalities included in each group is presented in the Table below:

Selected Municipalities

HIGH INCOME MUNICIPALITIES	LOW INCOME MUNICIPALITIES
Vitacura	Pedro Aguirre Cerda
	Pudahuel
	Conchalí
Providencia	Quilicura
	San Joaquín
	Lo Prado
La Reina	San Ramón
	Lo Espejo
	Renca
Las Condes	Recoleta
	San Bernardo
	La Granja
Ñuñoa	Cerro Navia
	El Bosque
	La Pintana

3.5 Classification and selection of names and surnames

The names and surnames were classified and selected according to the procedure used by Núñez and Gutiérrez (2004).

Specifically, a sample of names and surnames was taken from the alumni register of the Faculty of Economics and Business of the Universidad de Chile. Subsequently, a group of students was chosen, who classified (based on their personal perception) these names and surnames into: High Social Class, Middle Social Class and Lower Social Class.

For the purposes of the field work, only the names and surnames classified as Upper Class and Lower Class were considered.

An example of the surnames used in each category is presented in the Table below.

SELECTED SURNAMES

UPPER SOCIAL CLASS SURNAMES	LOWER SOCIAL CLASS SURNAMES
Rodrigo Recabarren Merino	Valeska Angulo Ortiz
Susan Abumohor Cassis	Pablo Ayulef Muñoz
Javiera Edwards Celis	Rosmary Becerra Fuentes
Pedro Ariztia Larrain	Clinton Benaldo Gonzalez

3.6 Description of the field work

The three people responsible indicated above handle the weekly selection of job vacancies that appear in "El Mercurio" on Sundays. They then construct the targeted CVs for each vacancy, with the most competitive CVs, ensuring their equivalence, in order to ensure that the only differentiating elements are the sex of the applicant, the social level, name and surname, and the municipality of residence.

Apart from the people in charge, the team is made up of three other assistants. This entire procedure is supervised directly by a Sociologist and an Economist who randomly reviews the CVs sent.

The job vacancies selected and the lot sent for each vacancy are entered weekly into a specially designed web page that allows all the vacancies to be reviewed, together with their respective sets of CVs. The entry of that information into the web page is handled by an I.T. expert.

A central aspect of this work is receiving the calls for the CVs sent. To receive these calls-responses, there is a fully dedicated man and woman team, ready to take the calls 24 hours a day from Monday to Sunday.

There are 8 mobile telephones, each with a different number, assigned to each of the CVs of the set; this ensures that the recruiters do not encounter repeated telephone numbers. The people in charge of receiving the calls record the day, name of the applicant, the vacancy and the phone number of the firm that selected the CV.

Each report is entered into the web page of the project, which allows for the regular supervision of the calls received.

In parallel, job vacancy responses are also received by e-mail. Some job vacancies request e-mails. For this, a generic e-mail has been created for each CV. To date, 54 e-mails addresses have been set up and they are checked every three days. As with the phone calls, the e-mails are reported and entered into the web page of the project.

3.7 Identity of the fictitious applicants

Once the names and surnames are classified by categories, Upper Class and Lower Class, they are then mixed so as to not use real names. Additionally, each fictitious applicant has an artificial RUT[12] and an exclusive e-mail address.

To ensure the equivalence of each set of CVs, the age of the applicants was set at between 30 and 35 years of age, married with between one and two children at most.

3.8 Ensuring the equivalence of the fictitious applicants between cells

In order to ensure the equivalence of the 8 fictitious applications sent for each vacancy, the other variables included in the CVs were controlled for similarity. For this, the following decisions were made:

- As regards the educational background of the applicants, those with university education are considered Universidad de Chile graduates and where necessary, they have postgraduate studies from the same University.

- The school of the applicant and the home address are determined by the municipality that they belong to. A bank of school names of each municipality is used for this. However, to ensure homogeneous schooling the 8 CVs sent must belong to the same category of socioeconomic background of the school[13].

- Additionally, each CV of the set of 8 has a unique telephone number different to the other seven; however, these may repeat themselves among different groups of CVs.

- The employment experience of the applicants is equivalent within each category (professional, technician, unskilled worker) but different among each other. Thus, professionals with greater time spent in the educational system have less years of employment experience, meanwhile, unskilled workers have a longer track record in the labor market. To maintain this equivalence, we have also set the number of jobs that each applicant has had in the various categories and their employment history continuity (absence of employment gaps).

[12] National Identification Number.

[13] This is a discrete variable which describe the level of income of the majority of the school population.

Category	Employment Experience	Number of jobs
Professionals	7 to 12 years	2 to 3
Technicians	8 to 13 years	4 to 5
Unskilled workers	12 to 17 years	5 to 7

- Postgraduate studies of applicants are equivalent within the set of 8 CVs that are sent for each vacancy. Within the set of 8 CVs, postgraduate studies must be from the same university (Universidad de Chile) and in very similar areas or even identical areas. Training courses must also be from equivalent institutions (Technical Insitutes) and in similar or identical areas.

- As a general rule, high quality CVs were sent for each vacancy. In other words, the variables of employment history, education and training were drawn up to be attractive to firms.

- The pay expectations required, which generally have to be included in job applications, were based on actual remuneration information of professionals and technicians (from the web page www.futurolaboral.cl). The starting point were pay levels required by a good candidate (of percentile 75 of that distribution) but, subsequently, the remuneration was reduced to average levels. Each set of 8 CVs sent for a vacancy had the same reference pay level and varied only slightly (in some cases it was given as a range and in others as a specific reference).

4 Findings

The CV mailing process started in the last week of March. As we can note from Table 1, on average, 68 vacancies have been applied for weekly, with a total of 11,016 CVs sent during the 20 weeks of the project, and a response rate of around 14.65%. This rate is somewhat higher than that obtained by Bertrand and Mullainathan (2004).

Table 1:
Distribution of Responses by Week

	Week	Total Number of Ads	Curriculums Sent	Total Number of Calls	General Response Rate
1	24 to 31 March	56	448	60	13.39%
2	3 to 9 April	63	504	71	14.09%
3	10 to 16 April	65	520	32	6.15%
4	17 to 23 April	61	488	60	12.30%
5	24 to 30 April	61	488	92	18.85%
6	1 to 7 May	67	536	132	24.63%
7	8 to 14 May	73	584	116	19.86%
8	15 to 21 May	72	576	75	13.02%
9	22 to 28 May	74	592	98	16.55%
10	29 May to 4 June	74	592	83	14.02%
11	5 to 11 June	72	576	135	23.44%
12	12 to 18 June	78	624	87	13.94%
13	19 to 25 June	73	584	90	15.41%
14	26 June to 02 July	76	608	77	12.66%
15	03 to 09 July	73	584	63	10.79%
16	10 to 16 July	69	552	84	15.22%
17	17 to 23 July	68	544	101	18.57%
18	24 to 30 July	75	600	93	15.50%
19	31 July to 6 August	66	528	45	8.52%
20	7 to 13 August	61	488	30	6.15%
	Average	69	551	81	14.65%
	Total	1377	11016	1624	

The response rate varies from week to week, probably depending on the labor market cycles and economic expectations during the year. There is evidence that this expectations has been declining from March until now.

Curriculums were sent to different job categories: professionals, technicians and unskilled workers. In the appendix we present a list of type of qualification within the different job categories. The average response rate by type of employment in Table 2 shows the same evolution as the response rate. We can also note that unskilled and technicians have a higher response rate than professionals. Professionals show a response rate of 12.1% compared to 14.2% for unskilled job announcements and 18.1% for technicians.

Table 2:
Number of CVs sent, Number of calls and Response rate by week and type of employment

	Number of Curriculums Sent			Number of Calls received			Response Rate		
Week	Professionals	Technicians	Unskilled	Professionals	Technicians	Unskilled	Professionals	Technicians	Unskilled
1 24 to 31 March	120	136	192	8	11	41	6.7%	8.1%	21.4%
2 3 to 9 April	176	168	160	7	18	46	4.0%	10.7%	28.8%
3 10 to 16 April	184	176	160	8	14	10	4.3%	8.0%	6.3%
4 17 to 23 April	168	160	160	2	21	37	1.2%	13.1%	23.1%
5 24 to 30 April	168	160	160	27	24	41	16.1%	15.0%	25.6%
6 1 to 7 May	200	176	160	34	63	35	17.0%	35.8%	21.9%
7 8 to 14 May	208	192	184	34	45	37	16.3%	23.4%	20.1%
8 15 to 21 May	192	200	184	22	32	21	11.5%	16.0%	11.4%
9 22 to 28 May	208	200	184	43	36	19	20.7%	18.0%	10.3%
10 29 May to 4 June	192	200	200	15	52	16	7.8%	26.0%	8.0%
11 5 to 11 June	176	192	208	64	34	37	36.4%	17.7%	17.8%
12 12 to 18 June	208	200	216	24	51	12	11.5%	25.5%	5.6%
13 19 to 25 June	192	192	200	19	43	28	9.9%	22.4%	14.0%
14 26 June to 02 July	216	192	200	35	34	8	16.2%	17.7%	4.0%
15 03 to 09 July	200	184	200	37	9	17	18.5%	4.9%	8.5%
16 10 to 16 July	168	184	200	23	39	22	13.7%	21.2%	11.0%
17 17 to 23 July	176	184	184	26	35	40	14.8%	19.0%	21.7%
18 24 to 30 July	208	192	200	19	52	22	9.1%	27.1%	11.0%
19 31 July to 6 August	192	136	200	5	16	24	2.6%	11.8%	12.0%
20 7 to 13 August	176	112	200		11	19	0.0%	9.8%	9.5%
Total	3728	3536	3752	452	640	532	12.1%	18.1%	14.2%

Calls were received after different number of days. However, the following graph shows that more than 60% were received before day 10. This graph was done based on a Table shown in the Appendix. The average number of days in answering was 12 days approximately for professionals and unskilled was 14 days and for technicians was 8 days (see Table 3).

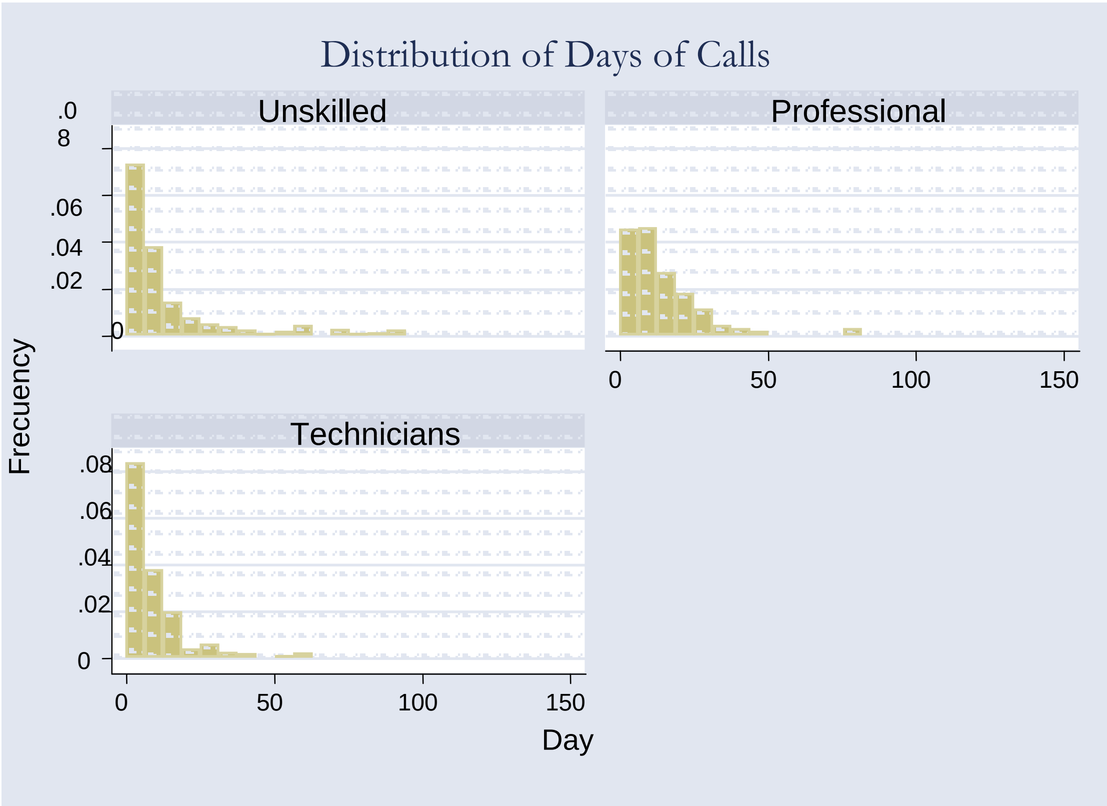


Table 3

Number of Days they lasted in calling back				
	Type of job			
Days	Professionals	Technicians	Unskilled	Total
Average Day	14,02	8,69	14,81	12,18
Total Calls Back	452	640	532	1624
Total CVs Sent	3728	3536	3752	11016
Response Rate	12,12%	18,10%	14,18%	14,74%

The resumes were sent by physical mail, email and fax. Table 4 shows the average number of days they lasted in making a call back by type of sending. We can see that CVs that were sent by physical mail received a call back in 18 days approximately and the ones sent by email received a call back in 8 days. The response to the fictitious candidates could have been done by telephone or by email.

Table 4

Number of Days they lasted in calling back				
	Way of sending them			
Days	Phisical Mail	Email	Fax	Total
Average	18,70	8,12	17,00	12,18
Total Calls Back	621	1001	2	1624
Total CVs Sent	3941	7059	16	11016
Response Rate	15,76%	14,18%	12,50%	14,74%

We will look at the average response rate by the three dimensions considered in this paper.

4.1 Gender Effects

If we take a look at the gender based information, the response rates show very similar levels: 14.9% for men and 14.6% for women. This difference is small and not statistically significant (applying a test where the null hypothesis is the equality of the two proportions). In other words, men and women seem to have the same probability of getting called to interview.

If the gender based difference is looked at in the response rates within the High Class group (by surnames), an slightly higher rate is obtained for women (15.3% vs 15.1%), in contrast to the situation with surnames in the Lower Classes were the response rates is higher for men (14.7% vs 14%). However, the differences are not statistically significant.

Table 5
Callbacks by Gender

		Men		Women		Differences			
	CVs Sent	Calls	Rate	Calls	Rate	Diff Calls	Diff Rate	Z	P-value
General									
All	5508	819	14.9%	805	14.6%	-14	-0.3%	0.376	0.707
Professionals	1864	232	12.4%	220	11.8%	-12	-0.6%	0.602	0.547
Technicians	1768	302	17.1%	338	19.1%	36	2.0%	-1.572	0.116
Unskilled	1876	285	15.2%	247	13.2%	-38	-2.0%	1.778	0.075
High Social Class									
All	2754	415	15.1%	420	15.3%	5	0.2%	-0.188	0.851
Professionals	932	115	12.3%	120	12.9%	5	0.5%	-0.349	0.727
Technicians	884	151	17.1%	166	18.8%	15	1.7%	-0.930	0.352
Unskilled	938	149	15.9%	134	14.3%	-15	-1.6%	0.968	0.333
Low Social Class									
All	2754	404	14.7%	385	14.0%	-19	-0.7%	0.731	0.465
Professionals	932	117	12.6%	100	10.7%	-17	-1.8%	1.228	0.219
Technicians	884	151	17.1%	172	19.5%	21	2.4%	-1.292	0.196
Unskilled	938	136	14.5%	113	12.0%	-23	-2.5%	1.565	0.118
High Income Mun.									
All	2754	421	15.3%	410	14.9%	-11	-0.4%	0.414	0.679
Professionals	932	116	12.4%	116	12.4%	0	0.0%	0.000	1.000
Technicians	884	159	18.0%	167	18.9%	8	0.9%	-0.491	0.623
Unskilled	938	146	15.6%	127	13.5%	-19	-2.0%	1.244	0.213
Low Income Mun.									
All	2754	398	14.5%	395	14.3%	-3	-0.1%	0.115	0.908
Professionals	932	116	12.4%	104	11.2%	-12	-1.3%	0.861	0.389
Technicians	884	143	16.2%	171	19.3%	28	3.2%	-1.742	0.082
Unskilled	938	139	14.8%	120	12.8%	-19	-2.0%	1.272	0.203

4.2 Neighborhood Effects

If we turn to the municipal dimension, the response rate of applicants from high income municipalities is 15.1%, compared to a rate of 14.4% for applicants from low income municipalities. These differences between municipalities, both on a general and on a cell level, are on average higher than that observed in the case of gender. However, this difference is not statistically significant to 90%.

Table 6
Callbacks by Municipality

		High Income Municipality		Low Income Municipality		Differences			
	CVs Sent	*Calls*	*Rate*	*Calls*	*Rate*	*Diff Calls*	*Diff Rate*	*Z*	*P-value*
General									
All	5508	831	15.1%	793	14.4%	-38	-0.7%	1.021	0.307
Professionals	1864	232	12.4%	220	11.8%	-12	-0.6%	0.602	0.547
Technicians	1768	326	18.4%	314	17.8%	-12	-0.7%	0.524	0.600
Unskilled	1876	273	14.6%	259	13.8%	-14	-0.7%	0.655	0.512
High Social Class									
All	2754	430	15.6%	401	14.6%	-29	-1.1%	1.092	0.275
Professionals	932	117	12.6%	118	12.7%	1	0.1%	-0.070	0.944
Technicians	884	163	18.4%	154	17.4%	-9	-1.0%	0.558	0.577
Unskilled	938	150	16.0%	133	14.2%	-17	-1.8%	1.097	0.273
Low Social Class									
All	2754	405	14.7%	388	14.1%	-17	-0.6%	0.652	0.514
Professionals	932	115	12.3%	102	10.9%	-13	-1.4%	0.939	0.348
Technicians	884	163	18.4%	160	18.1%	-3	-0.3%	0.185	0.853
Unskilled	938	123	13.1%	126	13.4%	3	0.3%	-0.204	0.838
Men									
All	2754	421	15.3%	398	14.5%	-23	-0.8%	0.871	0.384
Professionals	932	116	12.4%	116	12.4%	0	0.0%	0.000	1.000
Technicians	884	159	18.0%	167	18.9%	8	0.9%	-0.491	0.623
Unskilled	938	146	15.6%	127	13.5%	-19	-2.0%	1.244	0.213
Women									
All	2754	410	14.9%	395	14.3%	-15	-0.5%	0.572	0.567
Professionals	932	116	12.4%	104	11.2%	-12	-1.3%	0.861	0.389
Technicians	884	143	16.2%	171	19.3%	28	3.2%	-1.742	0.082
Unskilled	938	139	14.8%	120	12.8%	-19	-2.0%	1.272	0.203

4.3 Social Class Effect

A similar situation to the above may be observed when the response rates of fictitious candidates with Upper Class surnames (15.2%) are compared with those with Lower Class surnames (14.3%). Once again, the differences are not statistically significant. The largest differences occur within the group of women and also within the high income municipalities category.

A similar situation to the above may be observed when the response rates of fictitious candidates with Upper Class surnames (15.2%) are compared with those with Lower Class surnames (14.3%). Once again, the differences are not statistically significant. The largest differences occur within the group of women and also within the high income municipalities category.

Table 7
Callbacks by Surname

	CVs Sent	High Social Class Calls	High Social Class Rate	Low Social Class Calls	Low Social Class Rate	Differences Diff Calls	Differences Diff Rate	Test Z	Test P-value
General									
All	5508	835	15.2%	789	14.3%	-46	-0.8%	1.236	0.216
Professionals	1864	235	12.6%	217	11.6%	-18	-1.0%	0.903	0.367
Technicians	1768	317	17.9%	323	18.3%	6	0.3%	-0.262	0.793
Unskilled	1876	283	15.1%	249	13.3%	-34	-1.8%	1.591	0.112
High Income Mun.									
All	2754	430	15.6%	405	14.7%	-25	-0.9%	0.939	0.348
Professionals	932	117	12.6%	118	12.7%	1	0.1%	-0.070	0.944
Technicians	884	163	18.4%	154	17.4%	-9	-1.0%	0.558	0.577
Unskilled	938	150	16.0%	133	14.2%	-17	-1.8%	1.097	0.273
Low Income Mun.									
All	2754	401	14.6%	388	14.1%	-13	-0.5%	0.500	0.617
Professionals	932	115	12.3%	102	10.9%	-13	-1.4%	0.939	0.348
Technicians	884	163	18.4%	160	18.1%	-3	-0.3%	0.185	0.853
Unskilled	938	123	13.1%	126	13.4%	3	0.3%	-0.204	0.838
Men									
All	2754	415	15.1%	404	14.7%	-11	-0.4%	0.417	0.677
Professionals	932	115	12.3%	117	12.6%	2	0.2%	-0.140	0.889
Technicians	884	151	17.1%	151	17.1%	0	0.0%	0.000	1.000
Unskilled	938	149	15.9%	136	14.5%	-13	-1.4%	0.836	0.403
Women									
All	2754	420	15.3%	385	14.0%	-35	-1.3%	1.335	0.182
Professionals	932	120	12.9%	100	10.7%	-20	-2.1%	1.436	0.151
Technicians	884	166	18.8%	172	19.5%	6	0.7%	-0.363	0.717
Unskilled	938	134	14.3%	113	12.0%	-21	-2.2%	1.434	0.152

In conclusion, surprisingly, relevant gender differences are not found. In addition, the differences in response rates by municipalities or surnames are lower than the gender differences, in fact they are not statistically significant.

The analysis of the response rates for professionals confirms in general the aspects found above. There are no significant differences by gender, municipality or by surname.

4.4 Regression Analysis

Table 8 runs some complementary analysis using regression. As it can be seen, in none of the specifications there is a change in the main conclusions. The dummy variables associated to gender, municipality or surname are not significant.

Table 8

Regressions for the probability of receiving a callback
(Dependent Variable: Dummy=1 if a callback is received)

Variable	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Dummy High Income Municipality=1	0.0069	0.304	0.0070	0.301	0.0074	0.392	0.0048	0.736
Dummy Men=1	0.0026	0.706	0.0029	0.670	0.0020	0.770	-0.0106	0.389
Dummy High Class Surname=1	0.0082	0.222	0.0084	0.210	0.0082	0.226	-0.002	0.863
Dummy Professional Job ad=1			-0.0217	0.009	-0.0262	0.003	-0.0249	0.004
Dummy Technician Job ad=1			0.0380	0.000	0.0369	0.000	0.0370	0.000
Dummy Studied at Private School=1					-0.0030	0.780	-0.0114	0.741
Dummy Studied at Municipal School=1					-0.0173	0.038	0.0061	0.668
Controls for type of mail sent	No		No		Yes		Yes	
Including interactions	No		No		No		Yes	
Pseudo R2	0.0003		0.006		0.0189		0.009	
Number of observations	11016		11016		11016		11016	

Note: Probit Regressions. Coefficients are expressed in probability points for discrete changes of dummy variables from 0 to 1 (evaluated at means).

4.5 Timing of the callbacks

The results shown until now allow us to say that there are no differences in callback rates across groups. However, it could be possible to hypothesize differences favoring some groups in the timing of the callbacks.

This is not the case, however, as it is shown in.Table 9. All the differences reported in the number of days to receive a callback across groups are not statistically significant.

Table 9
Number of days to receive a callback

	Mean	Median
Gender:		
Men	12.8	8
Women	11.6	7
Difference	1.2	1
Municipality:		
High Income	11.8	7
Low Income	12.5	7
Difference	-0.7	0
Surname:		
High Class	12.3	7
Low Class	12.1	7
Difference	0.2	0

References

Adimark, "Mapa Socioeconómico de Chile. Nivel socioeconómico de los hogares del país basado en datos del Censo".

Anderson, Lisa; Roland Fryer and Charles Holt (2005). "Discrimination: Experimental Evidence from Psychology and Economics." Forthcoming in *Handbook on Economics and Discrimination*, William Rogers, Ed.

Antonovics, Kate; Peter Arcidiacono and Randy Walsh (2004). "Competing Against the Opposite Sex." *Economics Working Paper Series 2003-08,* University of California at San Diego.

Antonovics, Kate; Peter Arcidiacono and Randy Walsh (2005). "Games and Discrimination: Lessons from the Weakest Link." Forthcoming at *Journal of Human Resources.*

Altonji, Joseph and Rebecca Blank (1999). "Race and Gender in the Labor Market." *Handbook of Labor Economics, 3,* pp. 3143-3259.

Arenas, Alberto, Jere Behrman and David Bravo (2004) "Characteristics of and Determinants of the Density of Contributions in a Private Social Security System". Working Paper, Michigan Retirement, Research Center, May, 2004.

Becker, Gary (1971) The Economics of Discrimination, 2nd Edition, The University of Chicago Press, IL.

Becker, Gary (1991) A Treatise on the Family, enlarged edition: Harvard University Press, Cambridge, MA.

Bertrand, Marianne and Sendhil Mullainathan (2004). "Are Emily and Greg more Employable than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination." *American Economic Review*, 94(4), pp. 991-1013(23).

Blank, Rebecca; Marilyn Dabady and Constance Citro, Eds. (2004). "Measuring Racial Discrimination. Panel on Methods for Assessing Discrimination." The National Academies Press, Washington, D.C.

Blinder, Alan (1973). "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources, 7(4)*, pp. 436-55.

Bravo, David (2005) "Elaboración, Validación y Difusión de Índice Nacional de Calidad del Empleo Femenino", Centro de Microdatos, Universidad de Chile. Report prepared to the Secretary of Gender Sigues (Ministerio Servicio Nacional de la Mujer).

Bravo, David (2004), "Análisis y principales resultados. Primera Encuesta de Protecciòn Social". Departamento de Economía, Universidad de Chile y Ministerio del Trabajo y Previsiòn Social, Julio.

Contreras, Dante y Gonzalo Plaza (2004) "Participación Femenina en el Mercado Laboral Chileno. ¿Cuánto importan los factores culturales?", Departamento de Economía, Universidad de Chile

Contreras, Dante y Esteban Puentes (2001) "Is The Gender Wage Discrimination Decreasing In Chile? Thirty Years Of 'Robust' Evidence", Departamento de Economía, Universidad de Chile.

Fernandez, Fogli And Olivetti (2004) "Preference Formation And The Rise Of Women's Labor Force Participation: Evidence From WWII", NBER Working Paper 10589

Goldin, Claudia and Cecilia Rouse (2000). "Orchestrating Impartiality: The Impact of 'Blind' Auditions on Female Musicians." *American Economic Review 90(4),* pp. 715-741.

Heckman, James, and Peter Siegelman (1993). "The Urban Institute Audit Studies: Their Methods and Findings." In *Clear and Convincing Evidence: Measure of Discrimination in America.* Michael Fix and Raymond Struyk, editors. The Urban Institute Press, Washington D.C.

Heckman, James (1998). "Detecting Discrimination." *The Journal of Economic Perspectives,12(2)*, pp. 101-116.

Heckman, James, Jora Stixrud and Sergio Urzua (2005) "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior", University of Chicago.

Levitt, Steven (2004). "Testing Theories of Discrimination. Evidence from 'The Weakest Link.'" *Journal of Law and Economics*, 47, pp. 431-452.

List, John (2003). "The Nature and Extent of Discrimination in the Marketplace: Evidence from the Field." *Quarterly Journal of Economics*, 119(1), pp. 49-89.

Moreno, Martin; Hugo Ñopo, Jaime Saavedra and Maximo Torero (2004) "Gender and Racial Discrimination in Hiring. A Pseudo-Audit Study for Three Selected Occupations in Metropolitan Lima." *IZA Discussion Paper 979.*

Montenegro, Claudio (1999) "Wage distribution in Chile: Does Gender Matter? A Quantile Regression Approach. Mimeo, Universidad de Chile.

Montenegro, Claudio y Paredes, Ricardo (1999) "Gender Wage Gap and Discrimination: A Long Term View Using Quantile Regression". Mimeo, Universidad de Chile.

Neal, Derek A. and William R. and Johnson (1996) "The Role of Premarket Factors in Black-White Wage Differences", *The Journal of Political Economy*, Vol. 104, No. 5 (Oct., 1996), 869-895.

Newmark, David; Roy J. Bank and Kyle D. Van Nort (1996) "Sex Discrimination in Restaurant Hiring: An Audit Study", *The Quarterly Journal of Economics*, Vol. 111, No. 3 (Aug., 1996), 915-941.

Nuñez, Javier and Roberto Gutierrez (2004) "Classism, Discrimination and Meritocracy in the Labor Market: The Case of Chile." *Documento de trabajo 208*. Departamento de Economia, Universidad de Chile.

Ñopo, Hugo (2004). "Matching as a Tool to Decompose Wage Gaps." *IZA Discussion Paper No. 981*.

Oaxaca, Ronald (1973). "Male-Female Wage Differentials in Urban Labor Market." *International Economic Review*, 14(3), pp. 693-709.

O'Neil, June E. and Dave M. O'Neil (2005) "What do wage Differentials tell us about labor Market Discrimination", NBER Working Paper 11240.

Paredes, Ricardo y Riveros, Luis (1994): "Gender Wage Gaps in Chile. A Long term View:1958:1990". *Estudios de Economía*, Vol.21, Número especial, 1994.

Riach, Peter and Judith Rich (2002). "Field Experiments of Discrimination in the Marketplace." *The Economic Journal,112,* pp. 480-518.

Riach, Peter and Judith Rich (2004). "Deceptive Field Experiments of Discrimination: Are they Ethical?" *KYKLOS, 57(3),* pp. 457-470.

Rosenberg, M. (1965). Society and the Adolescent Self-Image. Princeton, NJ: Princeton University Press.

Rotter, J. B. (1966). Generalized Expectancies for Internal versus External Control of Reinforcement. Washington DC: American Psychological Association.

Appendix to Chapter 1

Table A.1

	Unskilled	
	Number	%
Administrativo	952	25.37
Aseador	208	5.54
Auxiliar Aseo	48	1.28
Bodeguero	384	10.23
Cajero	328	8.74
Cobrador	96	2.56
Conductor	32	0.85
Conductores	16	0.43
Digitador	368	9.81
Encuestador	88	2.35
Fotocopiador	8	0.21
Garzon	112	2.99
Garzón	40	1.07
Guardia	56	1.49
Operario Producción	8	0.21
Operario Tintoreria	8	0.21
Promotor	304	8.1
Recepcionista	8	0.21
Recepcionistas	8	0.21
Vendedor	624	16.63
Volantero	56	1.49
Total	3,752	100

Table A2

Professionals

	Number	%
Abogado	168	4.51
Abogado litigante	8	0.21
Abogado media Jornada	8	0.21
Abogado part-time	8	0.21
Constructor Civil	600	16.09
Constructor Civil (jefe proyecto)	8	0.21
Constructor Civil de Obra	8	0.21
Constructor Civil en altura	8	0.21
Contador Auditor	905	24.28
Contador Auditor Bilingüe	7	0.19
Ing. Civil Electronico	8	0.21
Ing. Civil Informatico	32	0.86
Ing. Civil Informático	48	1.29
Ing. Civil Telecomunicaciones	8	0.21
Ing. Comercial (Marketing)	8	0.21
Ing. Ejec. En Computacion	8	0.21
Ing.Comercial Marketing	8	0.21
Ingeniero Civil	104	2.79
Ingeniero Civil Computacion	16	0.43
Ingeniero Civil Constructor	8	0.21
Ingeniero Civil Industrial	24	0.64
Ingeniero Civil en Computacion	8	0.21
Ingeniero Comercial	552	14.81
Ingeniero Comercial MBA	8	0.21
Ingeniero Constructor	8	0.21
Ingeniero Ejec Informatico	16	0.43
Ingeniero Ejec. Informatico	24	0.64
Ingeniero Ejec. Informático	72	1.93
Ingeniero Electronico	8	0.21
Ingeniero Informatico	136	3.65
Ingeniero Informático	104	2.79
Ingeniero Informático (Teradata)	8	0.21
Ingeniero Obras Civiles	8	0.21
Ingeniero Telecomunicaciones	8	0.21
Ingeniero en Computacion	8	0.21
Ingeniero en Telecomunicacione:	8	0.21
Ingeniero, Const. Civil	8	0.21
Profesor	720	19.17
Psicologo	8	0.21
Psicólogo	8	0.21
Supervisor Educacional	8	0.21
Total	3728	100

Table A3

Technicians

	Number	%		Number	%
Soporte Computacional	8	0.23	Informático Hardware	8	0.23
Administrador	16	0.45	Jefe Adquisiciones	8	0.23
Administrador Empresas	8	0.23	Jefe Facturación	8	0.23
Administrador Sistema	8	0.23	Jefe de Abastecimiento	8	0.23
Administrador de Botilleria	8	0.23	Jefe de Bodega	8	0.23
Administrador de Empresas	8	0.23	Jefe de Local	56	1.58
Administrador de Local	16	0.45	Jefe de Locales	8	0.23
Administrador de Redes	16	0.45	Jefe de Personal	8	0.23
Administrador de Restaurant	8	0.23	Jefe de Recursos Humanos	8	0.23
Administrador de Sistemas	16	0.45	Jefe de Tienda	32	0.9
Administrador de red	8	0.23	Jefe de Tiendas	8	0.23
Administrador de redes	8	0.23	Jefe para cafeteria y pasteleria	8	0.23
Administrativo en Comex	8	0.23	Operador Informático	8	0.23
Adquisiciones	8	0.23	Paramedico	16	0.45
Agente de Ventas	16	0.45	Paramedico RX	8	0.23
Agente de Ventas Intangibles	8	0.23	Paramedicos	8	0.23
Analista Computacional	8	0.23	Pedidor Aduanero	8	0.23
Analista Programador	200	5.66	Prevencionista Riesgos	8	0.23
Analista Sistemas	8	0.23	Procurador	32	0.9
Analista de Sistema	32	0.9	Programador	544	15.38
Analista de Sistemas	24	0.68	Programador Analista	8	0.23
Analista o Programador	8	0.23	Programador Clipper	8	0.23
Asesor Comercial Marketing	8	0.23	Programador Web	80	2.26
Asistente Adquisiciones	16	0.45	Programador Webmaster	8	0.23
Asistente Comercio Exterior	8	0.23	Programador o Analista	8	0.23
Asistente Contable	40	1.13	Programador y Analistas	8	0.23
Asistente Técnico Hardware	8	0.23	Proyectista Autocard	8	0.23
Asistente de Enfermeria	8	0.23	Soporte	16	0.45
Asistente de Enfermos	16	0.45	Soporte Computacional	88	2.49
Auxiliar Enfermería	8	0.23	Soporte Informático	8	0.23
Auxiliar Paramedico	16	0.45	Soporte Tecnico	8	0.23
Auxiliar Paramédico	32	0.9	Soporte Técnico	24	0.68
Auxiliar Técnico de Laboratorio	8	0.23	Soporte en Redes	16	0.45
Auxiliar de Enfermeria	40	1.13	Supervisor	8	0.23
Auxiliar de Enfermería	40	1.13	Supervisor Cobranzas	24	0.68
Auxiliar de Laboratorio	8	0.23	Supervisor Locales Comerciales	8	0.23
Auxiliar de enfermería	8	0.23	Supervisor Logístico	16	0.45
Auxiliar de laboratorio	8	0.23	Supervisor de Call Center	8	0.23
Auxiliar de toma de muestra	8	0.23	Supervisor de Facturación y cobranzas	8	0.23
Ayudante Contable	8	0.23	Supervisor de Venta	8	0.23
Ayudante de Contador	40	1.13	Tecnico Informatico	8	0.23
Chef	32	0.9	Tecnico Paramedico	8	0.23
Cheff Ejecutivo	8	0.23	Tecnico Paramedicos	8	0.23
Comercio Exterior	8	0.23	Tecnico Soporte	16	0.45
Conocimientos en Computacion	8	0.23	Tecnico en Computación	8	0.23
Contador	200	5.66	Tecnico en Redes	8	0.23
Contador Administrador	8	0.23	Tecnico paramedico	8	0.23
Contador Asistente	16	0.45	Técnico Administración de Redes	8	0.23
Contador General	72	2.04	Técnico Administrador Empresas	8	0.23
Contador general	8	0.23	Técnico Comercio Exterior	32	0.9
Desarrollador de Web	8	0.23	Técnico Computación	16	0.45
Dibujante Autocad	48	1.36	Técnico Gastronómico	8	0.23
Dibujante Estructural	8	0.23	Técnico Informático	32	0.9
Dibujante Gráfico	8	0.23	Técnico Instalación Redes	8	0.23
Dibujante Mecánico Autocad	8	0.23	Técnico Jurídico	24	0.68
Dibujante Proyecticta	8	0.23	Técnico Paramédico	88	2.49
Dibujante Técnico	32	0.9	Técnico Prevención	8	0.23
Dibujante de Arquitectura	8	0.23	Técnico Programador	24	0.68
Dibujante técnico	24	0.68	Técnico Químico	8	0.23
Dibujante y Proyectistas	8	0.23	Técnico Soporte Terreno	8	0.23
Diseñador Gráfico	128	3.62	Técnico Soporte en Linux	8	0.23
Diseñador Industrial	32	0.9	Técnico de Comercio Exterior	8	0.23
Diseñador Internet	8	0.23	Técnico en Comercio Exterior	16	0.45
Diseñador Web	16	0.45	Técnico en Comex	8	0.23
Diseñador Web Master	8	0.23	Técnico en Computación	128	3.62
Diseñador de Página web	8	0.23	Técnico en Computación y Redes	8	0.23
Diseñador de web	8	0.23	Técnico en Enfermería	8	0.23
Ejecutivo Comercio Exterior	8	0.23	Técnico en Gastronomía	8	0.23
Ejecutivo Telemarketing	8	0.23	Técnico en Hardware y Redes	8	0.23
Ejecutivo de Ventas	8	0.23	Técnico en Hardware y Software	8	0.23
Encargado de Adquisiciones	16	0.45	Técnico en Informática	16	0.45
Encargado de Adquisisciones	8	0.23	Técnico en Logística	8	0.23
Encargado de Compras	8	0.23	Técnico en Mantención	8	0.23
Encargado de Informatica	8	0.23	Técnico en Programación	8	0.23
Encargado de Informática	8	0.23	Técnico en Redes Computacionales	8	0.23
Encargado de Local	8	0.23	Técnico en Reparación	8	0.23
Encargado de Remuneraciones	8	0.23	Técnico en Soporte	72	2.04
Encargado de comercio exterior	8	0.23	Técnico en Soporte Computacional	8	0.23
Encargado de informática	8	0.23	Técnico en comex	8	0.23
Encargado de remuneraciones	8	0.23	Técnico paramédico	8	0.23
Experto en Computación	8	0.23	Técnico pc grafico	8	0.23
Experto en Diseño Página Web	8	0.23	Vendedores Isapre	8	0.23
Explotador de Sistemas	8	0.23	Web Master	8	0.23
Informático	8	0.23	Total	1648	100

Table A4

Number of Days they lasted in calling back

Days	Type of job Professionals	Technicians	Unskilled	Total
0	10	90	54	154
1	55	92	65	212
2	11	57	45	113
3	10	36	44	90
4	3	19	15	37
5	14	20	7	41
6	26	22	15	63
7	19	58	50	127
8	31	50	21	102
9	26	23	28	77
10	17	11	22	50
11	31	5	4	40
12	7	5	2	14
13	11	5	5	21
14	24	28	15	67
15	9	24	11	44
16	12	13	11	36
17	9	7	5	21
18	11	3		14
19	2	2	1	5
20	15		2	17
21	7	4	12	23
22	13	4	7	24
23	5	1	3	9
24	9	5		14
26	1	9	1	11
27	18	4	3	25
28	3	6	5	14
29	1	3	2	6
30	9	1	5	15
31		1		1
32			1	1
33	1	9		10
34			4	4

35	2		1	3
36	7	1	1	9
37	2		5	7
38	3			3
40	2		1	3
41	2		5	7
42	1	1		2
43		4	1	5
44		2		2
48	2	2		4
49		1	1	2
50	3		2	5
51			4	4
52			1	1
54		4		4
55			1	1
57			4	4
58		1	8	9
59		3	2	5
64		1		1
66		3		3
73			4	4
74			4	4
76			1	1
77	5		2	7
84	3		1	4
85			2	2
86			1	1
90			2	2
91			4	4
93			1	1
95			1	1
98			1	1
105			2	2
111			1	1
116			1	1
125			1	1
126			1	1
Average Day	14,02	8,69	14,81	12,18
Total Calls Back	452	640	532	1624
Total CVs Sent	3728	3536	3752	11016
Response Rate	12,12%	18,10%	14,18%	14,74%

Table A5

Number of Days they lasted in calling back

Way of sending them

Days	Phisical Mail	Email	Fax	
0		154		154
1		212		212
2	4	109		113
3	47	43		90
4	26	11		37
5	16	25		41
6	19	44		63
7	66	61		127
8	54	48		102
9	61	16		77
10	21	29		50
11	19	21		40
12	2	12		14
13	4	17		21
14	27	40		67
15	29	15		44
16	20	16		36
17	9	10	2	21
18	10	4		14
19	3	2		5
20	10	7		17
21	11	12		23
22	17	7		24
23	5	4		9
24	11	3		14
26	9	2		11
27	6	19		25
28	8	6		14
29	5	1		6
30	14	1		15
31		1		1
32		1		1
33	1	9		10
34	4			4
35		3		3
36	4	5		9
37	7			7

38	2	1		3
40		3		3
41	6	1		7
42	2			2
43		5		5
44	2			2
48	2	2		4
49	2			2
50	2	3		5
51	4			4
52	1			1
54		4		4
55	1			1
57	4			4
58	8	1		9
59	3	2		5
64		1		1
66		3		3
73	4			4
74	4			4
76	1			1
77	7			7
84	3	1		4
85	2			2
86	1			1
90	2			2
91	4			4
93	1			1
95	1			1
98		1		1
105		2		2
111	1			1
116	1			1
125	1			1
126		1		1
Average	18,70	8,12	17,00	12,18
Total Calls Back	621	1001	2	1624
Total CVs Sent	3941	7059	16	11016
Response Rate	15,76%	14,18%	12,50%	14,74%

Chapter 2

"Is there labor market discrimination among professionals in Chile? Lawyers, Doctors and Business-people"

Abstract

This paper presents a complete analysis of the gender differences in three Chilean professionals labor market: Business, Law and Medicine. In the analysis, we utilize a new and rich data set collected for this effects. This data set contains information on labor market outcomes (including labor history), on schooling attainment and schooling performance, on a complete set of variables characterizing the family background of the individuals in the sample and on non cognitive abilities.

Our results show that differences in wages attributed to gender are only present in the Law profession. In the Business/Economics profession a vector of current family condition makes the gender effect disappear and in Medicine taking into account hours worked, size of the firm and region make also disappear the gender gap.

Specially important are shown to have a better level of self control in explaining wage differences.

1 Introduction

Labor market discrimination is said to arise when two identically productive workers are treated differently on the grounds of the worker's race or gender, when race or gender do not in themselves have an effect on productivity (Altonji and Blank, 1999; Heckman, 1998).

However, there are never identical individuals. There are several unobservable factors that determine individual performance in the labor market. First, we do not observe individual's cognitive abilities[14]. Second, we do not observe individual's non-cognitive abilities such as personal motivation, self-determination, and locus of internal/external control or self-confidence. Third, we do not observe pre-labor market discrimination conditions such as family background and school environment[15]. Fourth, we do not observe individual past expectations about how the labor market works[16].

Regarding gender group differences, these can be found for market and non-market activities and for types of jobs. There are gender differences for comparative advantages due to: differences in gender roles in home production, differences in parental investment in skills (Becker, 1991) and the transfer of family preferences (Fernandez, Fogli and Olivetti, 2004). And there are group gender differences in human capital investments as a result of pre-labor market discrimination. Consequently, discrimination can influence human capital investment before and after an individual enters the labor market.

Based on these facts and on the lack of studies in Chile which can face these issues, we implemented a survey on professionals from three different careers in Chile: Law, Medicine and Business, to analyze differences in their wages but reducing unobservable to a minimum. They have all passed a university entrance selection test. They are comparable in their academic formation. We have data on their university performance. We have data on their social and family background. We have applied tem a test on non-cognitive abilities. We have applied a survey to ask them real labor experience and family conditions now.

[14] Neal and Johnson (1996) is a good example of how unobserved factors could be driving the results. They study the role of pre-market factors in black-white wage differences controlling with a test administered to teenagers prepared to leave high school in the US. They found that the adult black-white wage gap primarily reflects a skills gap due to observable differences in family backgrounds and school environments.

[15] O'Neil and O'Neil (2005) find that differences in productivity-related factors account for most of the between-group wage differences in the year 2000 for the US. Differences in schooling and in skills developed in the home and in school, as measured by test scores, are important in explaining black/white wage gaps. But the gender differences in schooling and cognitive skills are quite small and explain little of the pay gap. Instead the gender gap is largely due to choices made by women and men concerning the amount of time and energy devoted to a career, as reflected in years of work experience, use of part-time work, and other workplace and job characteristics.

[16] See Altonji and Blank (1999) for a complete survey on race and gender discrimination and explanations of the underlying theories.

Based on this complete and new dataset we have taken a regression analysis approach to determine how much of the wage gap is left once the only difference among individuals is gender.

Research in Chile have been centered on the traditional Oaxaca decomposition (Oaxaca, 1973; Blinder, 1973). Paredes and Riveros (1993), estimate the endowment and discrimination effects for the period 1958-1990[17]. They provide evidence on discrimination against females during the whole period examined. Montenegro (1999) and Montenegro and Paredes (1999) analyze the gender wage differential by using quantile regression and the Oaxaca decomposition. The evidence also shows stable and systematic differences in the returns to education and to experience by gender along the conditional wage distribution. In addition, it is also shown that discrimination is higher for women with more education and experience. However, these conclusions of studies are limited. They lack several control variables, related to cognitive and non-cognitive abilities and school and family environments. In addition, preferences over non-market activities and experience of Chilean female workers could prove to be a very important unobservable factor.

More recently, Núñez and Gutiérrez (2004) study social class discrimination in Chile under the traditional Blinder-Oaxaca decomposition. They use a dataset that allows them to reduce the role of unobservable factors by limiting the population under study and having better measures of productivity as we do. However, this study has some limitations. One it is related to the collection of the data. The survey was carried out by postal mail and had a very low response rate, 30% approximately. Second, the survey was carried out on recently graduated college students of Economics[18] which does not allowed to detect the effects of labor experience. Third, it lacks of survey data on labor history and real experience, family characteristics and preferences. Fourth, the survey had a very small sample size.

This paper faces these limitations by surveying 1,500 Alumni of the Universidad de Chile from the following degree programs: 500 from Medicine, 500 from Law and 500 from Business/Economics. Half of each group are women and half are men. We subsequently analyze wage differences between women and men for each careers correcting the estimates for post graduate schooling, labor market experience, parents schooling, married conditions and cognitive abilities. Following recent literature (Heckman, Stixrud and Urzua, 2005) we took the Rotter (1966) and Rosemberg (1965) tests for non-cognitive abilities. We have run OLS regressions and ordered probit estimation to explain economic outcomes by a set of explanatory variables.

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[17] Contreras and Puentes (2001) extended the analyses to 1996.
[18] In Chile, high school students choose subjects, not colleges as in the US.

The results indicate that that differences in wages attributed to gender are only present in the Law profession. In the Business/Economics profession a vector of current family condition makes the gender effect disappear and in Medicine taking into account hours worked, size of the firm and region make also disappear the gender gap. Specially important are shown to have a better level of self control in explaining wage differences.

This structure of the paper is the following. Next section 2 present the econometric models. Section 3 presents the data and summary of the descriptive statistics. Section 4 presents the results and finally section 5 presents the conclusions.

2 The Econometric Models

In this section we will explain briefly the well known models in which it is usually study labor market discrimination.

We are using two different specifications: OLS estimation and an ordered probit estimation[19]. In each of these models we have a wage equation as a function of a set of different explanatory variables:

Model 1: OLS

$$\log w_i = \gamma F_i + \lambda_1 Exp + \lambda_2 Exp^2 + \lambda_3 N_i^{jobs} + J_i^{'}\Phi + X_i^{'}\delta + S_i^{'}\Gamma + T_i^{'}\Delta + H_i^{'}\Pi + \varepsilon_i$$

where F is a dummy variable that takes value 1 if female and 0 otherwise. Thus, the coefficient γ measured the perceptual difference in wages that is lower because individual i is female rather than male. In this setting, it is assumed that the market value in the same way the characteristics of the individuals.

Exp is years of real labor experience and Exp^2 is the squared. And N^{jobs} is the average number of parallel working activities each individual does in a year.

J' is a set of variables related to characteristics of the job, it contains a dummy variable for the level of responsibility in the job which take value 1 if the occupation is of high responsibility[20] and 0 otherwise, a dummy variable for a big firm that takes value 1 if the firm

[19] In a future version of this paper we will include a Oaxaca decomposition.

[20] An occupation is set to be of high responsibility if its occupation code is related to the following categories: members of the executive or legislative power and directives of public and private firms, such as managers of business and company directors.

has more than 500 workers and a dummy variable equals to 1 if the person works in the metropolitan region.

X' is a set of variables related to other personal characteristics such as a dummy variable that takes value 1 if the person has done a postgraduate course, university performance measured with a dummy variable that takes a value 1 if the person reproved a class and age.

S' is a set of variables related to the person socioeconomic background such as mother's and father's years of schooling and grades at secondary school[21].

T' contains two measures of non cognitive abilities explained later.

Finally, H' contains three measures of current family situation such as a dummy for married, number of children and a dummy for head of the household. An alternative specification would have been to have a Heckman model

Model 2: Ordered Probit Model

$$I_i = j \quad if \quad \alpha_{j+1} \le \phi Hrs_i + \gamma F_i + \lambda_1 Exp + \lambda_2 Exp^2 + \lambda_3 N_i^{jobs} + J'_i \Phi + X'_i \delta + S'_i \Gamma + T'_i \Delta + H'_i \Pi + \varepsilon_i < \alpha_j$$
$$where \quad j = 1, \ldots, 8$$

I_i is an indicator variable for the wage intervals and Hrs_i is the monthly hours worked by individual i.

3 The Data

In this section we present a comprehensive descriptive statistics of the variables collected in the survey and used in the estimations[22].

We will look at different statistics of labor market outcomes, performance at University, social and academic background, test for non cognitive abilities and current household status. Each of these variables is meant to explain in same way differences between observed gender gaps in wages.

[21] Grades is Chile go from 1 to 7, having an average of secondary school performance of 6 is distinction.
[22] The questionnaire and a complete field work resume are in the appendix.

We have collected approximately the same quantity of interviews for each type of degree (see Table 1). That is 500 observations for each type.

Table 1
All Sample

Type of Degree	Obs	%
Business	505	33.18
Law	506	33.25
Medicine	511	33.57
Total	1522	100

Table 2 shows the list of variables included in the regression for the degree of Business and Economics by gender.

Regarding labor outcomes we can see that there are gender differences on wages[23]. Women's monthly wage is 69% of men's monthly wage, these differences can also be observed in the tabulations of wage intervals. However, since women work less hours a month, women's hourly wage is only 81% of men's hourly wage, and this is 97% if we look at the logarithm. We also can note that female labor force participation is 81% and is lower than male labor force participation which is 97%. Women have less accumulated experience and have less parallel activities, although these differences are not high. 56% of men have a job of high responsibility while 43% of women have the same level of responsibility in the job. We can also observe that there are differences in the type of firm they work. 47% of men work in firms with more than 500 workers, while 60% of women do the same.

We can note that more 15% of less women do a post graduate degree, although women seems to have a better performance at University and at school (see grades). Mother's schooling is higher for women than for men. These latter may be related to the transmission of preferences. There are not differences in socioeconomic background between men and women. 8% of each group comes from a poor family and 15% of each group was raised in a uni-parental home.

As we said before, we also collected measures of non-cognitive abilities by taking the Rotter (1966) and Rosenberg (1965) tests for internal and external locus of control and self-esteem, respectively[24]. The lower the index the higher is the degree of self control or self esteem. We

[23] Exact wages were only reported for 20% of the sample approximately, however most people who did not give the exact amount gave an interval. Therefore we have assigned the maximum of the interval to the wage. We are anyway running ordered probit using the intervals of wages. There were also people who did not want to answer this question therefore we have less data for this variable.
[24] The tests are included in the questionnaire.

can note than in average women got a lower degree of self control but a higher degree of self esteem.

Finally, we think that measures of the current home situation could be important since it may reflect preferences for home production activities. We can see that although the number of children and the percentage of married men and women are the same only 28% of women are head of the household whereas 96% of men are in the same situation.

Table 2
Summary Statistics: Business/Economics

	Male			Female		
	Obs	Mean	SD	Obs	Mean	SD
Labor Market Outcomes						
Hourly Wage	211	12120.4	4760.4	182	9842.93	5695.5
Log(hourly wage)	211	9.33	0.40	182	9.07	0.53
Monthly Wage	211	2314882	905585	182	1602061	756934
Labor Market Participation	252	0.97	0.16	253	0.85	0.36
Monthly Hours worked	245	192.56	31.71	214	184.17	265.63
Real experience	252	17.50	5.31	253	16.96	4.54
Real experience squared	252	334.38	207.88	253	308.15	166.66
Mean of number jobs by year	252	1.05	0.34	253	1.00	0.32
Level of responsibility	245	0.56	0.50	214	0.43	0.50
Big Firm (>500w)	252	0.47	0.50	253	0.60	0.49
Metropolitan Region	252	0.92	0.27	253	0.93	0.25
Age	252	42.50	6.40	253	41.04	5.20
Performance at University						
Reprove any class==1	252	0.89	0.31	253	0.83	0.38
Post graduate schooling==1	252	0.47	0.50	253	0.32	0.47
Family Background						
Mother's years of schooling	248	12.95	3.20	249	13.34	3.25
Father's years of schooling	245	14.62	3.26	247	14.58	3.55
Grades in secondary school	245	60.21	4.06	252	63.64	2.74
Poor background==1	250	0.07	0.26	253	0.08	0.26
Uniparental home==1	252	0.16	0.37	253	0.15	0.35
Non Cognitive Abilities						
Self control test	247	1.34	0.41	248	1.42	0.43
Self esteem test	245	1.55	0.38	249	1.49	0.40
Family Status						
Number of children	247	2.26	1.59	246	2.28	1.39
Married==1	252	0.85	0.35	253	0.82	0.38
Head of the household==1	252	0.96	0.19	253	0.28	0.45
Wage Intervals (1USD=537CHP)		%			%	
Less than 372 USD						
Between 372 and 745 USD	1	0.47		2	1.1	
Between 745 and 1120 USD				7	3.85	
Between 1120 and 1490 USD	1	0.47		9	4.95	
Between 1490 and 1862	5	2.37		20	10.99	
Between 1862 and 2793 USD	19	9		39	21.43	
Between 2793 and 3725 USD	42	19.91		38	20.88	
Between 3725 and 4656 USD	42	19.91		32	17.58	
Between 4656 and 5587 USD	36	17.06		18	9.89	
More thab 5587 USD	65	30.81		17	9.34	
Total	211	100		182	100	

Table 3 shows the summary of the descriptive statistics for the degree of Law by gender.

In this case the gap in monthly wages is 68% approximately in favour of men. However, we can note that monthly hours worked by women are in average higher than hours worked by men and so the gap reduces to 71% in monthly hourly wage and to 96% if we look at the logarithm. We also can note that female labor force participation is 93% and is lower than male labor force participation which is 99%, both are higher than in case of business. Women have more accumulated experience and have slightly less parallel activities, although these differences are also not high. We can also observe that the proportion of lawyers in job positions with more responsibility is less than in the case of business/economics reaching only 4% and 5% respectively. We can also observe that there are differences in the type of firm they work. In this case, women also tend to work in big firms (51%) more than men (31%).

We can note that 63% of women and men that study law do post graduate degrees. Again women have a better performance at University and at school: a lower proportion of women reprove classes and they have higher grades at secondary school. Mother's and father's schooling are higher for women than for men. This may be again related to the transmission of preferences. Only 6% of women come from a family of poor background, whereas 17% of men are in the same situation. 20% of each group was raised in a uni-parental home.

The measures of non cognitive abilities behave in the same way. In average women got a lower degree of self control but a higher degree of self esteem.

Finally, regarding the measures of current home situation present the following characteristics. We can see that there are more differences between men and women in this case. Married rate is lower for lawyers in average and even lower for women, also the number of children is slightly lower for women. Although women head of the household are also less than men, this rate is higher for lawyers reaching 37% of them.

Table 3
Summary Statistics: Law

	Male			Female		
	Obs	Mean	SD	Obs	Mean	SD
Labor Market Outcomes						
Hourly Wage	182	11148.6	6598.35	183	7967.87	3765.2
Log(hourly wage)	182	9.17	0.57	183	8.84	0.63
Monthly Wage	182	2066832	1247710	183	1400567	645716
Labor Market Participation	249	0.99	0.09	257	0.93	0.25
Monthly Hours worked	247	230.61	419.98	240	265.85	600.07
Real experience	249	19.39	5.21	257	20.58	6.72
Real experience squared	249	402.99	228.13	257	468.37	310.19
Mean of number jobs by year	249	1.36	0.59	257	1.35	0.60
Level of responsibility	247	0.04	0.21	240	0.05	0.22
Big Firm (>500w)	249	0.31	0.46	257	0.51	0.50
Metropolitan Region	249	0.71	0.45	257	0.81	0.39
Age	246	44.39	7.14	256	44.79	7.16
Performance at University						
Reprove any class==1	249	0.26	0.44	257	0.16	0.37
Post graduate schooling==1	249	0.63	0.48	257	0.63	0.48
Family Background						
Mother's years of schooling	226	12.53	3.52	238	13.54	3.00
Father's years of schooling	231	13.83	3.92	236	15.11	3.12
Grades in secondary school	245	60.02	4.71	256	63.04	3.85
Poor background==1	247	0.17	0.38	254	0.06	0.24
Uniparental home==1	249	0.20	0.40	257	0.21	0.41
Non Cognitive Abilities						
Self control test	230	1.47	0.45	241	1.51	0.47
Self esteem test	240	1.52	0.38	251	1.47	0.36
Family Status						
Number of children	239	2.44	1.44	251	2.09	1.39
Married==1	249	0.84	0.37	257	0.67	0.47
Head of the household==1	249	0.99	0.11	257	0.37	0.48
Wage Intervals (1USD=537CHP)		%			%	
Less than 372 USD	2	1.1				
Between 372 and 745 USD	2	1.1		6	3.28	
Between 745 and 1120 USD	2	1.1		8	4.37	
Between 1120 and 1490 USD	7	3.85		15	8.2	
Between 1490 and 1862	11	6.04		20	10.93	
Between 1862 and 2793 USD	29	15.93		48	26.23	
Between 2793 and 3725 USD	34	18.68		37	20.22	
Between 3725 and 4656 USD	31	17.03		36	19.67	
Between 4656 and 5587 USD	19	10.44		10	5.46	
More thab 5587 USD	45	24.73		3	1.64	
Total	182	100		183	100	

Table 4 shows the summary of the descriptive statistics for the degree of Medicine by gender.

In this case the gap in monthly wages is 76% approximately in favour of men. This is lower than in the case of business/economics and law. In addition, we can note that monthly hours worked by women are in average lower than hours worked by men and so the gap reduces to 91% in monthly hourly wage and to 99% if we look at the logarithm. We also can note that female labor force participation is 97% and is lower than male labor force participation which is 100%, both are higher than in case of business and law. The accumulated experience in terms of years of experience and number of parallel activities of women and men are the same. We can also observe that the proportion of doctors in job positions with more responsibility is nearly null for both gender. We can also observe that there are not great differences in the type of firm they work. In this case, 90% of women work in big firms and 86% of men. This latter statistics is higher than in the case of business and law.

In addition, we can note that 97% of women and men that study medicine follow post graduate degrees. This latter may be related to obtaining of specialities. Again women have a slightly better performance at University and at school: a lower proportion of women reprove classes and they have higher grades at secondary school. Mother's and father's schooling are more similar among groups in this case and the level of parent's schooling is higher in comparison to the other to professions.

The measures of non cognitive abilities behave in the same way than the other to cases. In average women got a lower degree of self control but a higher degree of self esteem. It is worth noting that non cognitive abilities are higher in this professionals than in business and law.

Finally, regarding the measures of current home situation present the following characteristics. We can see that medical professionals observed in this sample have less children than the other professional and women doctors have less children than men doctors. Married rate is lower for women than for men, however men have a higher married rate than the other two professions and women have higher married rate than lawyers but lower than business women. Although, again only 31% of women are head of the household in contrast to 99% of men.

Table 4
Summary Statistics: Medicine

	Male			Female		
	Obs	Mean	SD	Obs	Mean	SD
Labor Market Outcomes						
Hourly Wage	232	8046.97	5852.7	224	7303.7	4719.2
Log(hourly wage)	232	8.80	0.61	224	8.73	0.58
Monthly Wage	232	1171624	770749	224	889950	560867
Labor Market Participation	255	1.00	0.06	256	0.97	0.16
Monthly Hours worked	254	152.33	54.64	249	144.61	250.10
Real experience	255	13.24	2.63	256	13.34	2.47
Real experience squared	255	182.07	94.40	256	184.05	65.73
Mean of number jobs by year	255	1.24	0.46	256	1.22	0.44
Level of responsibility	254	0.01	0.11	249	0.00	0.06
Big Firm (>500w)	255	0.86	0.34	256	0.90	0.30
Metropolitan Region	255	0.59	0.49	256	0.77	0.42
Age	254	38.55	3.33	256	38.75	2.73
Performance at University						
Reprove any class==1	255	0.16	0.37	256	0.20	0.40
Post graduate schooling==1	255	0.97	0.17	256	0.97	0.17
Family Background						
Mother's years of schooling	242	13.35	3.72	252	13.93	3.26
Father's years of schooling	241	14.42	3.94	252	15.04	3.84
Grades in secondary school	254	64.41	2.93	254	65.98	2.03
Poor background==1	253	0.21	0.41	256	0.12	0.32
Uniparental home==1	255	0.13	0.33	256	0.13	0.34
Non Cognitive Abilities						
Self control test	240	1.29	0.44	241	1.32	0.41
Self esteem test	244	1.33	0.36	253	1.29	0.32
Family Status						
Number of children	248	2.02	1.24	255	1.92	1.34
Married==1	255	0.87	0.33	256	0.74	0.44
Head of the household==1	255	0.99	0.09	256	0.31	0.46
Wage Intervals (1USD=537CHP)		%			%	
Less than 372 USD	3	1.29		3	1.34	
Between 372 and 745 USD	20	8.62		19	8.48	
Between 745 and 1120 USD	17	7.33		35	15.63	
Between 1120 and 1490 USD	19	8.19		32	14.29	
Between 1490 and 1862	30	12.93		46	20.54	
Between 1862 and 2793 USD	70	30.17		55	24.55	
Between 2793 and 3725 USD	39	16.81		18	8.04	
Between 3725 and 4656 USD	13	5.6		8	3.57	
Between 4656 and 5587 USD	7	3.02		3	1.34	
More thab 5587 USD	14	6.03		5	2.23	
Total	232	100		224	100	

4 The Results

Descriptive statistics presented before help us to shed some light in which are the determinants of wages in the labor market.

In this section we will use these measures to see whether once we take into account some of these differences we still have the gaps in wages we have in our data.

As we pointed out in section 2 we are using two different specifications: OLS estimation and an ordered probit estimation.

Tables 5, 6 and 7 present the results of the OLS regressions for each type of degree respectively. Regarding Business/Economics we can see that once the variables describe in the sections before are included the coefficient associated to the variable female start decreasing stadely until it turns to be not statistically significant in column 7. This latter column is the one including the vector of current family condition. This vector does not have a theoretical reason of why should be added in the wage equations however we added this variables in order to control for preferences of looking for certain types of jobs. Number of children and head of the household are positive and statistically significant. In fact, we know that being head of the household present additional responsibilities to finance household consumption.

Other important variables which are determinants of business people's wages are experience, the level of responsibility at the occupation, having a post graduate study and working in the metropolitan region. All these four variables add a premium on a professional's wage in Business/Economics career.

Regarding professionals in the Law degree we can note that just as before the coefficient associated to the dummy for female decreases steadily once different variables are added progressively until it turns not significant in column 7. In this case, only the number of children is a significant variable of the vector of current family conditions. However, this vector is picking up all the effect of gender.

It is also new that in this wage equation the non cognitive ability test for self control is statistically significant. That is the higher the level of self control the higher are the wages. This is interesting and very intuitive to think, since lawyers need special abilities to be good professionals. As before real experience, the level of responsibility and a post graduate course helps to have higher wages.

Regarding doctors we can note that female is never a negative issue in terms of wages. The only variables statistically significant in our regressions are the size of the firm in the sense that the bigger the number of workers in the firm the lower is the wage, and working outside the metropolitan region give doctors higher wages. This latter may be due to scarcity of these professionals in the rest of the country as well as special government premiums to doctors working outside the metropolitan region.

Table 5

OLS Regressions: Business/Economics, Dependent Variable=Log(Hourly Wage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.259**	-0.269**	-0.260**	-0.259**	-0.231**	-0.213**	-0.090
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.180)
Real experience		0.117**	0.111**	0.121**	0.090**	0.079**	0.060*
		(0.000)	(0.000)	(0.000)	(0.001)	(0.007)	(0.038)
Real experience squared		-0.003**	-0.003**	-0.003**	-0.002**	-0.002*	-0.001
		(0.000)	(0.000)	(0.000)	(0.005)	(0.043)	(0.125)
Mean of number jobs by year		0.033	0.040	0.005	0.025	0.029	0.041
		(0.808)	(0.766)	(0.970)	(0.847)	(0.830)	(0.751)
Level of responsibility			0.109*	0.119*	0.123**	0.121**	0.108*
			(0.021)	(0.011)	(0.007)	(0.009)	(0.018)
Big Firm (>500w)			-0.023	-0.036	-0.009	-0.006	-0.024
			(0.614)	(0.438)	(0.845)	(0.886)	(0.585)
Metropolitan Region			0.170*	0.164	0.156	0.195*	0.196*
			(0.048)	(0.055)	(0.056)	(0.018)	(0.016)
Post graduate schooling==1				0.110*	0.106*	0.107*	0.114*
				(0.019)	(0.020)	(0.021)	(0.012)
Reprove any class==1				-0.128	-0.105	-0.093	-0.102
				(0.051)	(0.097)	(0.144)	(0.105)
Age				-0.010	-0.009	-0.013	-0.014
				(0.200)	(0.228)	(0.084)	(0.054)
Mother's years of schooling					0.003	0.006	0.006
					(0.683)	(0.485)	(0.490)
Father's years of schooling					0.011	0.010	0.009
					(0.170)	(0.192)	(0.248)
Grades in secondary school					-0.004	-0.006	-0.003
					(0.579)	(0.411)	(0.633)
Poor background==1					-0.060	-0.077	-0.118
					(0.501)	(0.399)	(0.188)
Uniparental home==1					-0.016	-0.020	-0.015
					(0.798)	(0.758)	(0.809)
Self control test						-0.064	-0.036
						(0.247)	(0.499)
Self esteem test						0.010	0.011
						(0.870)	(0.854)
Married==1							0.085
							(0.213)
Number of children							0.051**
							(0.003)
Head of the household==1							0.196**
							(0.004)
Constant	9.327**	8.191**	8.054**	8.382**	8.641**	8.979**	8.703**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	393	393	393	393	374	365	360
R-squared	0.072	0.128	0.150	0.174	0.181	0.190	0.244

p values in parentheses

* significant at 5%; ** significant at 1%

Table 6
OLS Regressions: Law, Dependent Variable=Log(Hourly Wage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.327**	-0.304**	-0.284**	-0.326**	-0.359**	-0.331**	-0.234
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.056)
Real experience		0.027	0.024	0.047	0.041	0.026	0.001
		(0.322)	(0.373)	(0.096)	(0.166)	(0.376)	(0.970)
Real experience squared		-0.001	-0.001	-0.001	-0.001	-0.001	-0.000
		(0.120)	(0.137)	(0.153)	(0.255)	(0.337)	(0.828)
Mean of number jobs by year		0.054	0.056	0.057	0.028	0.071	0.090
		(0.492)	(0.482)	(0.465)	(0.742)	(0.423)	(0.316)
Level of responsibility			0.105	0.097	0.063	0.071	0.072
			(0.544)	(0.571)	(0.726)	(0.691)	(0.699)
Big Firm (>500w)			-0.084	-0.088	-0.088	-0.052	-0.050
			(0.205)	(0.181)	(0.220)	(0.472)	(0.494)
Metropolitan Region			-0.050	-0.054	-0.110	-0.122	-0.116
			(0.492)	(0.456)	(0.169)	(0.129)	(0.156)
Post graduate schooling==1				0.109	0.102	0.099	0.126
				(0.115)	(0.168)	(0.186)	(0.098)
Reprove any class==1				-0.045	-0.020	-0.048	-0.048
				(0.586)	(0.824)	(0.600)	(0.598)
Age				-0.021*	-0.021*	-0.012	-0.013
				(0.010)	(0.022)	(0.196)	(0.199)
Mother's years of schooling					0.014	0.015	0.013
					(0.304)	(0.270)	(0.338)
Father's years of schooling					0.013	0.016	0.015
					(0.308)	(0.205)	(0.257)
Grades in secondary school					-0.005	-0.004	-0.003
					(0.604)	(0.719)	(0.733)
Poor background==1					0.136	0.178	0.144
					(0.267)	(0.148)	(0.242)
Uniparental home==1					-0.146	-0.158	-0.147
					(0.098)	(0.079)	(0.104)
Self control test						-0.200**	-0.194**
						(0.007)	(0.010)
Self esteem test						0.051	0.062
						(0.599)	(0.525)
Married==1							0.058
							(0.584)
Number of children							0.069*
							(0.027)
Head of the household==1							0.103
							(0.396)
Constant	9.168**	8.944**	9.035**	9.485**	9.602**	9.433**	9.393**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	365	365	365	362	315	299	297
R-squared	0.069	0.085	0.091	0.122	0.165	0.182	0.202

p values in parentheses
* significant at 5%; ** significant at 1%

Table 7

OLS Regressions: Medicine, Dependent Variable=Log(Hourly Wage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.067	-0.071	-0.019	-0.012	-0.024	-0.009	0.109
	(0.225)	(0.208)	(0.733)	(0.829)	(0.684)	(0.886)	(0.221)
Real experience		-0.032	-0.014	-0.026	-0.074	-0.081	-0.087
		(0.799)	(0.910)	(0.839)	(0.562)	(0.533)	(0.503)
Real experience squared		0.002	0.001	0.001	0.003	0.003	0.003
		(0.739)	(0.848)	(0.791)	(0.580)	(0.529)	(0.518)
Mean of number jobs by year		-0.062	-0.056	-0.055	0.019	0.002	-0.009
		(0.380)	(0.419)	(0.423)	(0.790)	(0.976)	(0.896)
Level of responsibility			0.130	0.119	0.085	0.083	0.096
			(0.662)	(0.688)	(0.773)	(0.776)	(0.741)
Big Firm (>500w)			-0.355**	-0.362**	-0.344**	-0.350**	-0.378**
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Metropolitan Region			-0.182**	-0.187**	-0.176**	-0.179**	-0.162**
			(0.002)	(0.002)	(0.004)	(0.004)	(0.010)
Post graduate schooling==1				-0.048	-0.115	-0.199	-0.218
				(0.781)	(0.532)	(0.305)	(0.260)
Reprove any class==1				-0.059	-0.058	-0.074	-0.047
				(0.429)	(0.438)	(0.333)	(0.548)
Age				0.002	0.011	0.007	0.005
				(0.890)	(0.495)	(0.656)	(0.776)
Mother's years of schooling					0.002	0.004	0.003
					(0.853)	(0.663)	(0.767)
Father's years of schooling					0.011	0.009	0.010
					(0.215)	(0.339)	(0.288)
Grades in secondary school					0.006	0.004	0.005
					(0.607)	(0.698)	(0.683)
Poor background==1					-0.014	-0.032	-0.045
					(0.860)	(0.684)	(0.561)
Uniparental home==1					-0.089	-0.075	-0.079
					(0.292)	(0.383)	(0.358)
Self control test						-0.081	-0.073
						(0.212)	(0.272)
Self esteem test						-0.040	-0.036
						(0.643)	(0.677)
Married==1							0.062
							(0.453)
Number of children							0.045
							(0.084)
Head of the household==1							0.162
							(0.075)
Constant	8.801**	9.021**	9.304**	9.365**	8.813**	9.343**	9.219**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	456	456	456	455	431	411	409
R-squared	0.003	0.005	0.072	0.075	0.075	0.081	0.097

p values in parentheses

* significant at 5%; ** significant at 1%

Tables 8, 9 and 10 present the results of the Ordered Probit regressions for each type of degree respectively. We think this model is more accurate because we did not have the real level of wages as a continuous variables for most of the sample.

Regarding Business/Economics we can see that it is still the case that once the control variables are included the coefficient associated to the variable female decreases to turn into to zero in column 7. Again, the vector of current family conditions is driving this result.

It is also maintained the conclusion that the other important variables are experience, the level of responsibility at the occupation, having a post graduate study and working in the metropolitan region. At the same time, performance at University and the self control non cognitive ability test are significant variables with the expected coefficients.

Regarding professionals in the Law degree we can note that contrary to the case above women lawyers do have a cost in terms of wages because of being women. In this model, there is strong significance of metropolitan region and age which are negative, and the self control test is again statistically significant. Lawyers who have a better level of self control got higher wages. It is maintained also that the number of children and being had of the household are important variables in the wage equation whereas in this case this vector is not picking up the effect of gender.

Regarding doctors the results are again very intuitive. We can observed that female turns to be a statistically not significant variable explaining wages. The size of the firm, working outside the metropolitan region and hours worked are statistically significant variables. It is also true that self control and family conditions are also statistically significant variables.

Table 8
Ordered Probit Regressions: Business/Economics, Dependent Variable=Wage Intervals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.867**	-0.924**	-0.926**	-0.938**	-0.698**	-0.643**	-0.341
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.053)
Monthly Hours Worked	0.000	0.000	0.000	0.000	0.011**	0.012**	0.012**
	(0.417)	(0.161)	(0.389)	(0.292)	(0.000)	(0.000)	(0.000)
Real experience		0.286**	0.273**	0.303**	0.263**	0.238**	0.210**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.005)
Real experience squared		-0.006**	-0.006**	-0.006**	-0.006**	-0.005*	-0.004*
		(0.000)	(0.000)	(0.000)	(0.001)	(0.013)	(0.029)
Mean of number jobs by year		-0.257	-0.261	-0.356	-0.145	-0.061	-0.033
		(0.408)	(0.402)	(0.256)	(0.665)	(0.857)	(0.923)
Level of responsibility			0.476**	0.500**	0.414**	0.416**	0.402**
			(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Big Firm (>500w)			0.262*	0.234*	0.155	0.164	0.137
			(0.016)	(0.033)	(0.176)	(0.157)	(0.241)
Metropolitan Region			0.345	0.344	0.324	0.453*	0.467*
			(0.086)	(0.088)	(0.116)	(0.031)	(0.027)
Post graduate schooling==1				0.263*	0.297**	0.283*	0.312**
				(0.017)	(0.010)	(0.016)	(0.009)
Reprove any class==1				-0.354*	-0.356*	-0.319	-0.356*
				(0.023)	(0.027)	(0.050)	(0.032)
Age				-0.015	-0.017	-0.030	-0.033
				(0.423)	(0.367)	(0.118)	(0.083)
Mother's years of schooling					0.000	0.008	0.007
					(0.997)	(0.710)	(0.735)
Father's years of schooling					0.036	0.036	0.035
					(0.073)	(0.069)	(0.083)
Grades in secondary school					-0.012	-0.019	-0.015
					(0.487)	(0.279)	(0.394)
Poor background==1					-0.255	-0.262	-0.387
					(0.248)	(0.244)	(0.092)
Uniparental home==1					-0.054	-0.068	-0.063
					(0.732)	(0.668)	(0.693)
Self control test						-0.326*	-0.275*
						(0.018)	(0.048)
Self esteem test						0.019	0.028
						(0.902)	(0.858)
Married==1							0.137
							(0.435)
Number of children							0.108*
							(0.018)
Head of the household==1							0.526**
							(0.002)
Observations	393	393	393	393	374	365	360

p values in parentheses
* significant at 5%; ** significant at 1%

Table 9

Ordered Probit Regressions: Law, Dependent Variable=Wage Intervals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.723**	-0.710**	-0.681**	-0.792**	-0.935**	-0.899**	-0.568**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)
Monthly Hours Worked	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.136)	(0.136)	(0.136)	(0.155)	(0.155)	(0.067)	(0.088)
Real experience		0.052	0.047	0.102*	0.107*	0.083	0.015
		(0.262)	(0.316)	(0.036)	(0.035)	(0.114)	(0.785)
Real experience squared		-0.002	-0.001	-0.001	-0.001	-0.001	0.000
		(0.140)	(0.166)	(0.210)	(0.276)	(0.369)	(0.776)
Mean of number jobs by year		-0.071	-0.065	-0.054	-0.136	-0.051	-0.010
		(0.599)	(0.630)	(0.690)	(0.361)	(0.745)	(0.948)
Level of responsibility			0.418	0.409	0.285	0.302	0.435
			(0.163)	(0.176)	(0.368)	(0.341)	(0.193)
Big Firm (>500w)			-0.030	-0.033	-0.029	0.034	0.026
			(0.790)	(0.775)	(0.816)	(0.790)	(0.841)
Metropolitan Region			-0.167	-0.189	-0.299*	-0.323*	-0.355*
			(0.181)	(0.136)	(0.031)	(0.023)	(0.014)
Post graduate schooling==1				0.151	0.120	0.118	0.166
				(0.208)	(0.349)	(0.369)	(0.216)
Reprove any class==1				-0.088	-0.033	-0.100	-0.109
				(0.536)	(0.829)	(0.530)	(0.500)
Age				-0.057**	-0.059**	-0.044**	-0.047**
				(0.000)	(0.000)	(0.009)	(0.006)
Mother's years of schooling					0.040	0.040	0.033
					(0.081)	(0.086)	(0.166)
Father's years of schooling					0.022	0.028	0.030
					(0.317)	(0.201)	(0.186)
Grades in secondary school					0.007	0.010	0.009
					(0.690)	(0.559)	(0.587)
Poor background==1					0.183	0.257	0.163
					(0.391)	(0.238)	(0.456)
Uniparental home==1					-0.235	-0.273	-0.283
					(0.128)	(0.087)	(0.079)
Self control test						-0.326*	-0.351**
						(0.012)	(0.008)
Self esteem test						0.160	0.184
						(0.347)	(0.285)
Married==1							-0.002
							(0.991)
Number of children							0.170**
							(0.002)
Head of the household==1							0.463*
							(0.028)
Observations	365	365	365	362	315	299	297

p values in parentheses

* significant at 5%; ** significant at 1%

Table 10

Ordered Probit Regressions: Medicine, Dependent Variable=Wage Intervals

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female==1	-0.401**	-0.412**	-0.315**	-0.312**	-0.120	-0.095	0.214
	(0.000)	(0.000)	(0.002)	(0.002)	(0.283)	(0.407)	(0.201)
Monthly Hours Worked	0.001**	0.001**	0.001**	0.001**	0.013**	0.013**	0.013**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Real experience		-0.064	-0.051	-0.056	-0.066	-0.070	-0.076
		(0.769)	(0.818)	(0.801)	(0.776)	(0.773)	(0.754)
Real experience squared		0.004	0.003	0.003	0.003	0.003	0.003
		(0.646)	(0.695)	(0.694)	(0.766)	(0.733)	(0.740)
Mean of number jobs by year		-0.265*	-0.259*	-0.270*	-0.021	-0.060	-0.087
		(0.030)	(0.036)	(0.029)	(0.875)	(0.654)	(0.520)
Level of responsibility			0.541	0.559	0.074	0.053	0.094
			(0.301)	(0.287)	(0.890)	(0.922)	(0.862)
Big Firm (>500w)			-0.522**	-0.521**	-0.591**	-0.637**	-0.722**
			(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Metropolitan Region			-0.426**	-0.429**	-0.380**	-0.385**	-0.349**
			(0.000)	(0.000)	(0.001)	(0.001)	(0.003)
Post graduate schooling==1				0.112	-0.125	-0.371	-0.407
				(0.714)	(0.711)	(0.304)	(0.261)
Reprove any class==1				0.065	-0.057	-0.100	-0.045
				(0.627)	(0.678)	(0.482)	(0.758)
Age				0.002	0.025	0.019	0.014
				(0.939)	(0.407)	(0.548)	(0.668)
Mother's years of schooling					0.007	0.012	0.009
					(0.696)	(0.525)	(0.658)
Father's years of schooling					0.018	0.015	0.018
					(0.282)	(0.395)	(0.308)
Grades in secondary school					0.002	-0.002	-0.002
					(0.910)	(0.924)	(0.926)
Poor background==1					-0.011	-0.053	-0.082
					(0.937)	(0.715)	(0.573)
Uniparental home==1					-0.156	-0.141	-0.152
					(0.317)	(0.380)	(0.347)
Self control test						-0.306*	-0.301*
						(0.011)	(0.016)
Self esteem test						-0.057	-0.053
						(0.726)	(0.744)
Married==1							0.076
							(0.624)
Number of children							0.101*
							(0.038)
Head of the household==1							0.445**
							(0.009)
Observations	456	456	456	455	431	411	409

p values in parentheses

* significant at 5%; ** significant at 1%

5 Conclusions

This paper study differences in wages of three types of professionals in Chile: Business women and men, lawyers and doctors.

Our preferred specification is an ordered probit model. In this specification we can see that female does seem to have only a negative effect on wages for lawyers, even including current family conditions. Business women and men differences disappear once the vector of current family conditions are added. And doctors seems to have no differences in wages due to gender.

Other important variables explaining differences in wages are the level of responsibility in the job, having postgraduate studies, the size of the firm, a regional effect. And most importantly, there is an important and positive effect of the non cognitive ability test that measures self control.

References

Altonji, Joseph and Rebecca Blank (1999). "Race and Gender in the Labor Market." *Handbook of Labor Economics, 3,* pp. 3143-3259.

Becker, Gary (1971) The Economics of Discrimination, 2nd Edition, The University of Chicago Press, IL.

Becker, Gary (1991) A Treatise on the Family, enlarged edition: Harvard University Press, Cambridge, MA.

Blinder, Alan (1973). "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources, 7(4)*, pp. 436-55.

Contreras, Dante y Esteban Puentes (2001) "Is The Gender Wage Discrimination Decreasing In Chile? Thirty Years Of 'Robust' Evidence", Departamento de Economía, Universidad de Chile.

Fernandez, Fogli And Olivetti (2004) "Preference Formation And The Rise Of Women's Labor Force Participation: Evidence From WWII", NBER Working Paper 10589

Heckman, James (1998). "Detecting Discrimination." *The Journal of Economic Perspectives,12(2)*, pp. 101-116.

Heckman, James, Jora Stixrud and Sergio Urzua (2005) "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior", University of Chicago.

Montenegro, Claudio (1999) "Wage distribution in Chile: Does Gender Matter? A Quantile Regression Approach. Mimeo, Universidad de Chile.

Montenegro, Claudio y Paredes, Ricardo (1999) "Gender Wage Gap and Discrimination: A Long Term View Using Quantile Regression". Mimeo, Universidad de Chile.

Neal, Derek A. and William R. and Johnson (1996) "The Role of Premarket Factors in Black-White Wage Differences", *The Journal of Political Economy*, Vol. 104, No. 5 (Oct., 1996), 869-895.

Nuñez, Javier and Roberto Gutierrez (2004) "Classism, Discrimination and Meritocracy in the Labor Market: The Case of Chile." *Documento de trabajo 208*. Departamento de Economia, Universidad de Chile.

Oaxaca, Ronald (1973). "Male-Female Wage Differentials in Urban Labor Market." *International Economic Review*, 14(3), pp. 693-709.

O'Neil, June E. and Dave M. O'Neil (2005) "What do wage Differentials tell us about labor Market Discrimination", NBER Working Paper 11240.

Paredes, Ricardo y Riveros, Luis (1994): "Gender Wage Gaps in Chile. A Long term View:1958:1990". *Estudios de Economía*, Vol.21, Número especial, 1994.

Rosenberg, M. (1965). Society and the Adolescent Self-Image. Princeton, NJ: Princeton University Press.

Rotter, J. B. (1966). Generalized Expectancies for Internal versus External Control of Reinforcement. Washington DC: American Psychological Association.

Appendix to Chapter 2

This survey was applied to ex-alumni of the Universidad de Chile that studied Medicine, Law and Business/Economics and who graduated at least eight years ago. The sample is made up of 50% men and 50% women.

The survey was implemented by telephone. To offer the respondents an image of the survey, a website has been designed to present the Survey, which provides a description of the survey, its objectives and questionnaires.

The survey takes approximately 20 minutes and contains six modules: General Information, Education, Employment History, Family Background, Individual History and Test of Non-Cognitive Abilities.

A1. Calendar of Activities

The following table shows the Calendar of Activities developed for the implementation of the Survey:

Date	Activity
December, 2005-January, 2006	Design of the Questionnaire Sample framework: to locate the address of the students in the university records
20th January	Progress Report and Work Plan
10th February	Videoconference
March, 2006	Design of the Questionnaire Sample framework: to locate the address of the students in the university records
April, 2006	Design of the Questionnaire Sample framework: to locate the address of the students in the university records
May, 2006	Pilot Survey Final questionnaire Questionnaire Manual for Interviewers Interviewer Training Survey Starts Data Entry and Validation of the Survey Starts
30th May	First draft
June, 2006	Survey Continues Data Entry and Validation of the Survey Continues

20th June	Workshop
July, 2006	Survey Continues Data Entry and Validation of the Survey Continues
6th September	Second draft Data Entry and Validation of the Survey Continues
20th October	Final Workshop
29th November	Final version

A2. Sample Design

The survey is being developed without geographic restrictions. Since it is a telephone based survey, there are no geographic boundaries. It is simply a case of locating the individuals of the sample in the city where they may be.

The selection process of the sample was developed in the following stages.

A3. Search for Names of Ex-alumni

First, a search was made for administrative information on ex-alumni in the Faculties of the Universidad de Chile and centrally. We had several meetings with Central authorities of the University who finally accepted to furnish us with a database of graduates of the University from 1970 to 1997 from the three degree programs involved. This database is confidential and contains the national identification number of the person, their name, year of graduation, degree program and, in some cases, an address.

Table 1 shows the distribution of the original framework sample, obtained from the administrative information of the Universidad de Chile.

Table 1: Original Framework Sample

Year	Economics Female	Economics Male	Economics Sub total	Law Female	Law Male	Law Sub total	Medicine Female	Medicine Male	Medicine Sub total	Total
1970	27	90	117	56	153	209	36	181	217	543
1971	14	74	88	41	139	180	42	164	206	474
1972	20	98	118	50	132	182	48	158	206	506
1973	28	98	126	56	119	175	41	158	199	500
1974	61	186	247	44	113	157	50	178	228	632
1975	37	123	160	36	135	171	80	209	289	620
1976	41	168	209	52	107	159	90	165	255	623
1977	20	112	132	30	68	98	115	240	355	585
1978	28	83	111	27	91	118	138	231	369	598
1979	35	152	187	27	106	133	206	376	582	902
1980	26	99	125	58	165	223	98	156	254	602
1981	52	132	184	64	111	175	165	233	398	757
1982	72	189	261	42	118	160	125	204	329	750
1983	69	191	260	53	112	165	142	273	415	840
1984	21	98	119	72	120	192	123	226	349	660
1985	41	182	223	43	137	180	115	235	350	753
1986	36	125	161	46	107	153	74	152	226	540
1987	34	103	137	28	85	113	80	212	292	542
1988	59	98	157	30	87	117	89	159	248	522
1989	46	97	143	32	84	116	103	167	270	529
1990	89	140	229	28	93	121	111	161	272	622
1991	80	136	216	23	78	101	98	155	253	570
1992	85	109	194	39	115	154	86	131	217	565
1993	49	53	102	52	133	185	88	147	235	522
1994	51	94	145	45	115	160	97	168	265	570
1995	46	67	113	62	106	168	72	133	205	486
1996	32	74	106	87	125	212	91	132	223	541
1997	46	84	130	76	140	216	87	132	219	565
Total	1245	3255	4500	1299	3194	4493	2690	5236	7926	16919

A4. Updating Ex-alumni Data

The addresses and other personal data on ex-alumni obtained from the administrative data showed a significant proportion of incomplete records with outdated information.

In order to update the original information, 6,000 individuals were chosen, who were tracked down in phone books and other sources to get their location data. After this search process, the following distribution was obtained (See Table 2). This will finally be the real sample framework from which the final sample is chosen.

Table 2: Real Sample Framework

Year	Economics Female	Economics Male	Economics Sub total	Law Female	Law Male	Law Sub total	Medicine Female	Medicine Male	Medicine Sub total	Total
1982				42	118	160				160
1983	69	191	260	53	112	165				425
1984	21	98	119	72	120	192				311
1985	41	182	223	43	137	180				403
1986	36	125	161	46	107	153				314
1987	34	103	137	28	85	113				250
1988	59	98	157	30	87	117				274
1989	46	97	143	32	84	116				259
1990	89	140	229	28	93	121	111	161	272	622
1991	80	136	216	23	78	101	98	155	253	570
1992	85	109	194	39	115	154	86	131	217	565
1993	49	53	102	52	133	185	88	147	235	522
1994	51	94	145	45	115	160	97	168	265	570
1995	46	67	113	62	106	168	72	133	205	486
1996	32	74	106	87	125	212	91	132	223	541
1997	46	84	130	76	140	216	87	132	219	565
Total	784	1651	2435	758	1755	2513	730	1159	1889	6837

A5. Selection of the Sample

The definitive sample is chosen based on the real sample framework defined in the point above.

The objective number of surveys for carrying out is 1,500. One third of these correspond to each degree program, and in equivalent proportions between men and women.

In order to effectively obtain the surveys requested, it is necessary to have an over-sized-sample, to be able to cover the losses arising from people that cannot be found or that refuse to participate in the survey. Based on earlier studies and considering the lack of individual information available, we can consider a loss of 100%. Therefore, the selected sample should be 3,000 individuals.

The selected sample is obtained by choosing 1,000 individuals graduated in each of the three degree programs (Law, Medicine and Economics) randomly. The same number of men and women are chosen within each degree program.

To complete the sample, by degree program, the same number of male and female graduates by graduation year are chosen. Therefore, the final sample, displayed in Table 3, may be characterized as probabilistic, stratified by degree programs and gender, with a non-proportional distribution among strata.

Table 3: Final Sample

	Economics			Law			Medicine			Total
Year	**Female**	**Male**	**Sub total**	**Female**	**Male**	**Sub total**	**Female**	**Male**	**Sub total**	
1987				28	37	65				65
1988				30	38	68				68
1989	46	60	106	32	36	68				174
1990	89	86	175	28	40	68				243
1991	80	83	163	23	34	57				220
1992	85	67	152	39	50	89	86	81	167	408
1993	49	33	82	52	57	109	88	91	179	370
1994	51	57	108	45	50	95	97	104	201	404
1995	46	42	88	62	46	108	72	82	154	350
1996	32	45	77	87	54	141	91	81	172	390
1997	46	51	97	76	60	136	87	82	169	402
Total	524	524	1048	502	502	1004	521	521	1042	3094

A6. Pilot survey

Before implementing the survey, a pilot survey was carried out on the whole sample selected. The general objective of this pilot survey is to evaluate the operation of the questionnaire by means of a telephone interview. It also has the following specific objectives:

1. Review problems of content (difficulty of comprehension on the part of the respondents, lack of response categories, etc.).
2. Evaluate the implementation periods.
3. Difficulty in contacting and locating respondents.

To carry out the Pre-Test, a sample of graduates that were not included in the selected sample were extracted, from 70 cases of each of the degree programs chosen for the study. These 70 cases were in turn divided evenly among men and women.

Table 4: Sample Pre-Test

Degree program	Men	Women	Total
Law	35	35	70
Medicine	35	35	70
Economics	35	36	71
Total	105	106	211

The Field Coordinator and the Survey Programmer were responsible for the training of the telephone operators that carried out the pilot survey.

The training consisted of a presentation of the study, which was followed by a review of the questionnaire. It was carried out in the morning of the first day of work of the operators

After the end of the pilot survey, the questionnaire was modified slightly to gather the observations made through the implementation.

A7. Questionnaire and Interviewer Manual

The Survey is designed for telephone as well as paper based implementation, in case an interviewer should have to implement it so.

The Questionnaire that will finally be implemented is presented in the Appendix to this chapter of the Report and is comprised of 5 modules of questions and two non-cognitive ability tests that are to be found at the end there. The form covers areas such as: household structure and identification, income, job, education, health, housing, family background and perceptions. The modules are as follows:

- Module A: General Information of the Respondent
  Objective: Obtain information on sex, marital status, age and position within the household.

- Module B: Education
  Objective: Obtain Information on prior education of the respondent and also on activities subsequent to university. Questions are posed on the quality of the secondary education received.

- Module C: Employment History
  Objective: Obtain complete information on the respondents employment activities from their date of graduation. They are also questioned on their parallel activities and job characteristics. For those who are currently inactive, questions are posed to obtain information on the reserve salary.
  This allows us to discover the real employment experience of men and women.

- Module D: Family Background
  Objective: Obtain information about the parents' education and the emotional and socioeconomic stability of the household during childhood. There are also questions on the size of household, gender composition and education level of siblings.

- Module E: Personal History
  Objective: Obtain information on respondent's marital history and common-law wives, as well as children.

- Test 1: Rotter Internal-External Locus of Control Scale
  It is a four-item abbreviated version of a 23-item forced choice questionnaire adapted from the 60-item Rotter scale developed by Rotter (1966). The scale is designed to measure the extent to which individuals believe they have control over their lives, i.e., self-motivation and self-determination, (internal control) as opposed to the extent that the environment (i.e., chance, fate, luck) controls their lives (external control). The scale is scored in the internal direction: the higher the score, the more internal the individual. Individuals are first shown two sets of statements and asked which of the two statements is closer to their own opinion. They are then asked whether that statement is much closer or slightly closer to their opinion. These responses are used to generate four-point scales for each of the paired items, which are then averaged to create one Rotter Scale score for each individual.

- Test 2 Rosenberg Self-Esteem Scale
  It is a 10-item scale, designed for adolescents and adults; measures an individual's degree of approval or disapproval toward himself (Rosenberg, 1965). The scale is short, widely used, and has accumulated evidence of validity and reliability. It contains 10 statements of self-approval and disapproval to which respondents are asked to strongly agree, agree, disagree, or strongly disagree.

A8. Preparation of the Survey

Fieldwork preparation requires carrying out all the regular tasks, in other words, registration, training, supervision, as well as preparing and providing the necessary material and inputs for survey implementation.

The selection method for the interviewers was by invitation. These invitations were made to interviewers that have worked in other similar surveys undertaken previously by the Centro de Microdatos. In fact, 10 telephone interviewers were invited, who possessed previous training in the same characteristics as the Pilot survey. In this particular occassion, they also received an Interviewer Manual. All operators who implemented the survey have higher education studies, either technical level or university.

The training activity took approximately 4 hours. All the questions of the questionnaire were reviewed, and the concepts required to implement it were defined, as well as the aspects that had to be emphasized in the survey, in addition to the clarification of any pertinent queries.

A product of this stage was the Interviewer Manual with all the final corrections.

A9. Organization of the Work Team

The fieldwork team is finally composed of:

- A technical coordinator of the Survey, responsible for ensuring the correct implementation of the methodology and quality standards. He/she is responsible for verifying the correct implementation in the field, fulfillment of the sample sizes, and the subsequent verification of the control tabulations for the final approval of the database.

- A logistics and control coordinator, responsible for the correct execution and control of the administrative and financial processes. Responsible for monitoring the state of progress and ensuring observance of the work calendar.

- A field work coordinator, responsible for distributing the sample among the telephone operators and supervising the work carried out by them.

- An I.T. coordinator, responsible for designing, implementing and administering the information systems for monitoring field work, data entry of surveys, data validation and structuring the final magnetic file.

- A sample designer, responsible for creating the sample design and subsequent calculation of the expansion factors. Ernesto Castillo.

The Centro de Microdatos was responsible for preparing all the necessary inputs for the implementation of the survey, training classrooms, telephones, offices, office supplies, manuals and forms, transport and personnel.

Finally, the Survey is final database for analysis was available on October 25th.

Chapter 3

"Ability, Schooling Choices and Gender Labor Market Discrimination: Evidence for Chile"

Abstract

This paper presents a comprehensive analysis of the gender differences in the Chilean labor market. We formally deal with the selection of the individuals into schooling levels and its consequences on the gender gaps. Our approach allows for the presence of not only heterogeneity in observable variables but also unobserved heterogeneity. We link this unobserved heterogeneity to unobserved scholastic ability. In the analysis, we utilize a new and rich data set for Chile. This data set contains information on labor market outcomes (including labor history), on schooling attainment and schooling performance, and on a complete set of variables characterizing the family background of the individuals in the sample

Our results show that there exist statistically significant gender differences in several dimensions of the Chilean labor market. Nevertheless, we show that these gaps critically depend on the schooling level of the individuals considered in the analysis. For example, the results indicate that there are no gender differences in labor market variables among college graduates (except in the case of hourly wages).

We interpret our results with prudence. Specifically, instead of interpreting our findings as decisive evidence of the existence of discrimination in the Chilean labor market, we argue that future research based on better information might indeed explain some of the unexplained labor market gaps presented in this paper. In this context, our results represent a new and important attempt to provide a full understanding of the structural causes of gender gaps in the Chilean labor market but they are not conclusive.

1 Introduction

Gender gaps in a variety of labor and educational outcomes (e.g. wages, earnings, employment, schooling levels) are well documented. The structural reasons behind these gaps, however, are not fully understood.

This paper contributes to the literature by studying gender differences in a framework in which schooling decisions and labor market outcomes are endogenously determined. Our framework also allows individual heterogeneity not only from the point of view of observable characteristics but also unobserved variables. We assume that individuals know this additional source of heterogeneity, and they base their schooling and labor market decisions on it. Unobserved heterogeneity plays a crucial role in our approach.

Ours is a challenging task for several reasons. First, a comprehensive analysis of gender differences in a variety of outcomes is subject to the usual and irremediable data limitations. Second, the natural complexity associated with econometric models of multiple, endogenous, and correlated outcomes makes these models usually not very empirically appealing. And finally, the fact that we allow individuals decisions to depend on variables unobserved by the researcher but known to the agent represents an additional challenge of our approach. Nevertheless, we deal with each of these difficulties. First, we utilize a new data set from Chile that contains detailed information on labor market and schooling outcomes at the individual level. Second, we postulate a simple factor structure model based on economic theory that simplifies the manner we can deal with multiple endogenous variables. And finally, we interpret this factor as unobserved heterogeneity since the researcher does not need to know the individual factor (although it is assumed to be known by the individual). We argue that the factor represents a combination of different scholastic skills (cognitive and noncognitive skills).

As previously mentioned, we implement our approach using new information from Chile. The Chilean case provides an interesting example of apparently huge gender gaps in different dimensions of the labor market. Table 1 presents basic information for a variety of schooling and labor market outcomes obtained from a sample of males and females with ages between 28 and 40 years.[25]

The evidence in Table 1 provides an initial flavor of the gender differences that motivate the idea of this paper. A comparison of the schooling outcomes (Panel A

[25] The information comes from the Social Protection Survey 2002 of Chile (SPS02) which is the source of information used in this paper. This survey is described in detail in Section 2.

in Table 1) leads to conclude that, in average, (i) women are slightly more educated than males, (ii) women are less likely to repeat a grade in both primary and secondary school, and (iii) women show a better performance in school than males (measured by the average grade in secondary school). However, this educational advantage of women over men seems to have no consequences on the labor market. The evidence in Panel B illustrates this point. It shows that males overwhelmingly dominate females in every single dimension of the labor market (monthly earnings, employment, and experience).

This paper studies the factors explaining these gender differences in labor market and schooling outcomes.

The paper is organized as follows. Section 2 describes the data. Section 3 presents evidence on the differences in labor market outcomes between males and females using a conventional approach. Section 4 introduces our model and discusses its empirical implementation. Section 5 presents a discussion of our results. Section 6 concludes.

2 Data

This paper uses information from the Chilean Social Protection Survey 2002 (SPS02). This survey was designed to identify and analyze the most important determinants of the social security decisions (participation in the social security system) among Chileans. In order to do this, a representative sample of 17,246 participants of the Chilean pension system was interviewed between June of 2002 and January of 2003. For each individual in the sample, the survey collected information on household composition (ages, genders and schooling levels of the household members as well as their relations with the interviewee), current employment status, different sources of income, schooling (maximum schooling attained, average grades in primary and secondary school, characteristics of the primary and secondary school attended), family history (mother's and father's education, characteristics of the place of residence where the individual grew up, and number of previous relationships), labor history since age 15 or since 1980 depending on the year the individual became 15 years old (periods of employment, unemployment and inactivity), training programs (information on the three most important training programs since 1980), expectations (job, retirement and life), savings (instruments and amounts), and a set of variables describing the individual's knowledge of the characteristics and performance of the Chilean pension system.

We use a sample of individuals with ages in the range of 28 and 40 years. This group represents approximately the 21% of the original sample (3,566 versus 17,246). [26]

We restrict the ages of sample for several reasons. First, since the information on labor history begins only in 1980 (or since age 15), by using individuals 28-40 years old we assure that our sample report complete labor histories from age 18. Second, since schooling is an important ingredient of our analysis, by excluding individuals 27 years old and younger we focus our attention on individuals that have most likely reached their final schooling level.[27]

Finally, it is worth noting that the current Chilean schooling system was designed only in the early 80s. Therefore, since our analysis includes information on the characteristics of the primary and secondary schools in which the individual was enrolled, by restricting the analysis to the individuals with ages 28-40, we assure that such information is available for most of our sample.

Table A.1 presents the summary statistics of the variables used in this paper.

3 The Conventional Gender Gap Analysis

The gender differences in labor market outcomes are usually analyzed in the context of linear models in which the variable of interested is regressed on the gender dummy variable and set of additional controls. The coefficient associated with the gender dummy is interpreted as the estimated gender gap. Given its popularity, our first attempt to quantify gender gaps follows closely this idea. Table 2 presents the results from the following model of (log) hourly wages (lnW):

[26] Our sample is obtained after considering the following exclusions. We first exclude the military sample (57 individuals) and individuals reporting as occupation "family member without salary" (12 individuals). Then, we exclude individuals 27 years old or younger and 41 years old or older. With this the sample reduces from 17,177 to 5,439. Finally, individuals with missing values in any of the following variables are excluded: "years of education", "mother's education", "father's education", "growing up in poverty" and "growing up in a single parent household". This exclusion reduces the sample to the final 3,566 individuals. It is worth noting that the final exclusion is required since for each individual we need to have valid values for the controls entering in the schooling decision model presented in Section 3.1.

[27] A more general analysis of the schooling decisions would require a dynamic model for schooling choices. The SPS02 does not allow us to carry out such analysis.

$$\ln W = \alpha + \varphi\, Gender + \beta X + U \qquad (1)$$

where *Gender* represents the gender dummy (*Gender*=1 if individual is Male and 0 if Females), X represents individual's observable characteristics, and U is the error term in the regression. In this simple model, the (conditional) gender gap is simply φ. Each column in Table 2 represents a different specification of (1). In particular, column (A) presents the results of a model in which we include the characteristics of both the place of residence and occupation in the vector of controls X. Column (B) adds a set of variables controlling for the individual's accumulated experience and column (C) adds to the controls in (B) a set of variables controlling for schooling levels. The results indicate that males make approximately 23% more than females in terms of hourly wages. This gender gap is statistically significant regardless of the column analyzed.

The last model in Table 1 (column D) includes a correction for the fact that the labor market outcome is reported only for individuals working (Heckman, 1974). This is particularly important given the gender differences in employment rates reported in Table 1 (panel B). Thus, the model in column D is:

$$\ln W = \alpha + \varphi\, Gender + \beta X + U \text{ if wage is observed } (D=1)$$
$$D = 1[\gamma Z + V > 0] \qquad (2)$$

where 1[A] is an indicator function that takes a value of 1 if A is true and zero otherwise, Z is a vector of observables and V represents the unobservables. D=1[.] is the censoring rule for wages. In Z we include variables such as number of children, whether or not the individual grew up in a poor household, mother's and father's occupational status. The estimated gap after correcting for selection is 29% and it is statistically significant. Thus, after controlling for selections, we not only find a significant but larger gender gap in wages (compare to the ones estimated without using the correction). This fact illustrates the importance of paying particular attention to individual's endogenous decisions (in this case employment decisions) when analyzing gender gaps. We exploit this point in the following section.

The analysis of gender gaps in wages is interesting and important but it represents only one dimension of many among which males and females can differ. We first extend our analysis to the case of monthly hours worked. We model (log) hours worked using a linear-in-parameter models similar to (1) and the same set of controls as the ones utilized for wages. Table 3 presents the estimates of gender gaps in this case. The structure of this table is identical to the one in Table 2. The results from columns (A), (B) and (C) suggest that males work approximately 11% more hours per month than females. This difference is statistically significant and it is stable across the three specifications. However, the last column in Table 3 presents (again) a different story. Unlike the results for wages, the correction for selection significantly reduces the gender gap in hours worked. The estimated gap is only 0.04% and it is not statistically significant.

We also extend our analysis to employment status. In this case, we use a probit model instead of a linear regression model. Table 4 presents the results for three different specifications. For each specification, we present both estimated coefficients and estimated marginal effects.[28] The results indicate that males are 22% more likely to report an employment (during the month previous to the date of the interview) than females when schooling and experience are excluded as controls. When schooling or schooling and experience are included as controls the estimated gap is 14%. The gaps are statistically significant regardless of the specification.

In summary, the results show that men dominate women in every labor market outcome. Additionally, the results are robust across different specifications and only in the case of hours worked and after controlling for selection we find neither sizeable nor statistically significant gender differences.

Notice that up this point we have utilized the individual's schooling decisions and accumulated experience as exogenous regressors. However, in principle these variables can also be subject to gender differences. Tables 5 and 6 present evidence on this point. The implications of separate analyses of schooling choices and accumulated experience on our previous results are left for the next section where they are discussed in the context of a more general framework than the one used here.[29]

We model accumulated experience assuming that, whatever experience level is observed in the sample, it is the result of a decision involving three alternatives: less than 10 years of experience, between 10 and 15 years of experience, and more than 15 years of experience. This decision is assumed to depend on the schooling level of the individual as well as on his family background (mother's and father's education, broken home, age, and growing up in poverty). Given this set up, we compute the gender gaps in accumulated experience by estimating a multinomial probit model. Table 5 presents the estimated coefficients and marginal effects.

[28] The marginal effects are computed at the mean values of the variables in the model.

[29] This is particularly important if we consider that schooling decisions and accumulated experience are probably endogenous variables in the context of the models presented in Tables 2, 3 and 4. The model presents in the next section deals with this possibility.

The estimates associated with the gender dummy are all significant and suggest that males are considerably more likely to report more experience than females. Specifically, males are 40% less likely to report less than 10 years of experience and 29% more likely to report more than 15 years of experience than females.

The analysis of gender differences in schooling decisions is also relevant in the context of the previous results. On the one hand, if males are in fact more likely to report higher schooling levels than females (after controlling for observable characteristics), then the gender differences in labor market outcomes (including accumulated experience) could be simply interpreted as the result of gender differences in accumulated human capital. On the contrary, if females are more likely to report higher schooling levels than males, then the estimated gender differences in labor market outcomes could be interpreted as downward biased estimates of the actual gaps.

Table 6 sheds light on existence of gender gaps in schooling decisions. It presents the coefficients and marginal effects obtained from a multinomial schooling choice model. The model is estimated using the maximum schooling levels reported by the individuals in the sample. The schooling levels considered are: primary school, secondary school, some post-secondary education, and complete tertiary education (college graduates). The results show that (if anything) females are more likely than males to reach higher schooling levels.

The advantage of females over males in schooling achievement/attainment is confirmed in Table 7. This table presents the estimated gender gaps for three variables measuring schooling performance: probability of a grade repeated during primary school, probability of a grade repeated during secondary school, and average grades during secondary school. For each variable we consistently observe that females outperform males. Males are 7% and 4% more likely to repeat a grade during primary and secondary school, respectively, and males in average have a significantly lower grades during high school than females (0.31 points of test's standard deviation).

Therefore, the evidence presented in Tables 6 and 7 leads us to conclude that females should be better prepared than males to face the labor market. This also implies that by not including the gender differences in schooling variables our previous results might be underestimating the actual unexplained gender gaps (or discrimination). We analyze this possibility by introducing a more general model in which schooling decisions, schooling achievement, employment decisions, accumulated experience, hours worked and hourly wages are modeled jointly.

4 A Model of Schooling and Labor Market Outcomes under Unobserved Heterogeneity

The model in this section follows the analysis in Heckman, Stixrud and Urzua (2006). Heckman, Stixrud and Urzua (2006) postulate and estimate a model with two underlying sources of unobserved heterogeneity that they interpreted as abilities (cognitive and noncognitive abilities). Conditioning on the observables, these factors account for all of the dependence across choices in the model. They show that both abilities play a crucial role explaining a variety of labor market and behavioral outcomes.

In this paper we postulate the existence of only one underlying factor representing unobserved heterogeneity. This is mainly due to the fact that we do not have a set of cognitive and noncognitive variables in the SPS02 sample. Consequently, we interpret the source of unobserved heterogeneity as a combination of both cognitive and noncognitive abilities.[30] The identification of its distribution is discussed in Section 3.4 below.

Let θ denote the unobserved heterogeneity or latent ability. We assume this latent ability determines the individual's schooling and labor market outcomes, and that there are not intrinsic differences between males and females regarding θ, so that we can work with an overall distribution for θ.[31]

4.1 The Model for Schooling

Each agent chooses the level of schooling, among $\overline{S}$ possibilities, such that he maximizes his benefit. Let I_s represent the net benefit associated with each schooling level s (s={1,…, $\overline{S}$ }) and assume the following linear-in-the-parameters model for I_s:

$$I_s = \varphi_s Gender + \beta_s X_s + \alpha_s \theta + e_s \quad \text{for } s = 1,\ldots,\overline{S} \qquad (3)$$

[30] We expect to extend our model to a multi-factor model in which we can precisely distinguish between cognitive and noncognitive abilities.

[31] The alternative would have been the estimation of gender specific distributions. We consider this an attractive possibility. However, given the data limitations (sample size) and the large number of parameters in the model, we prefer to follow a simple analysis by considering an overall distribution for θ. Future research should consider the potential differences in unobserved heterogeneity between males and females.

here φ_s represents the gender gap associated with the schooling level s, X_s is a vector of observed variables determining schooling, β_s is the associated vector of parameters, α_s is the factor loading associated with the latent ability, and e_s represents an idiosyncratic component assumed to be independent of θ, and X_s. The individual components $\{e_s\}_{s=1}^{\bar{S}}$ are mutually independent. All of the dependence across schooling choices comes through the observable, X_s, and the latent ability θ.

The agent chooses the level of schooling with the highest benefit. Formally,

$$s^* = \underset{s \in \{1,\ldots,\bar{S}\}}{\operatorname{argmax}} \{I_s\} \qquad (4)$$

where s^* denotes the individual's chosen schooling level. Notice that conditional on X_s (with $s = 1,\ldots,\bar{S}$) and θ, equations (3) and (4) can be interpreted as a standard discrete choice model.

4.2 The Model for Accumulated Experience

The model also treats accumulated experience as an endogenous outcome. Specifically, after deciding the schooling levels, agents are assumed to pick their experience levels $\bar{A}$ different alternatives. As in the schooling model, given the schooling level s, we assume a linear-in-the-parameters specification for the benefits associated with the experience level a(s) $(I_{a(s)})$:

$$I_{a(s)} = \varphi_{a(s)} Gender + \beta_{a(s)} X_a + \alpha_{a(s)} \theta + e_{a(s)} \qquad \text{for } a(s) = 1,\ldots,\bar{A} \text{ and } s=1,\ldots,\bar{S}$$

where $\varphi_{a(s)}$ is the gender gap, X_a is the vector of observed variables, $\beta_{a(s)}$ is the associated vector of parameters, $\alpha_{a(s)}$ is the factor loading, and $e_{a(s)}$ represents an idiosyncratic component assumed to be independent of θ, and X_a. The individual components $\{e_{a(s)}\}_{a=1}^{\bar{A}}$ for any s are mutually independent. Finally, the observed experience level $A^*(s^*)$ (where s^* represents the schooling level observed in the data) is interpreted as

$$A^*(s^*) = \underset{a(s^*)\in\{1,\ldots,\overline{A}\}}{\arg\max}\{I_{a(s)}\}.$$

4.3 The Model for Hourly Wages and Monthly Hours Worked

For hourly wages and monthly hours worked, we consider schooling/experience specific models. Consider first the model for wages. Denote by *s* and *a(s)* the schooling and experience level attained by the individual. Wages ($Y_{a(s)}$) are modeled using a linear specification:

$$\ln Y_{a(s)} = \varphi_{Y,a(s)} Gender + \beta_{Y,a(s)} X_Y + \alpha_{Y,a(s)}\theta + e_{Y,a(s)} \quad \text{for } s = 1,\ldots,\overline{S} \text{ and } a(s) = 1,\ldots,\overline{A}$$

where $\varphi_{a(s)}$ is the gender gap, X_Y is a vector of observed controls, $\beta_{Y,a(s)}$ is the vector of coefficients, $\alpha_{a(s)}$ is the coefficient associated with the latent ability, and $e_{Y,a(s)}$ represents an idiosyncratic error term such that $e_{Y,a(s)} \perp (\theta, X_Y)$ for any $a(s)(=1,\ldots,\overline{A})$ and $s(=1,\ldots,\overline{S})$.

A parallel strategy is used to model hours worked. Let $H_{a(s)}$ denote the monthly hours worked given schooling level *s* and experience level *a(s)*. Thus, we assume

$$\ln H_{a(s)} = \varphi_{H,a(s)} Gender + \beta_{H,a(s)} X_H + \alpha_{H,a(s)}\theta + e_{a(s)} \quad \text{for } s = 1,\ldots,\overline{S} \text{ and } a(s) = 1,\ldots,\overline{A}$$

where $\varphi_{H,a(s)}$ is the gender gap, X_H is a vector of observed controls, $\beta_{H,a(s)}$ is the vector of coefficients associated with X_H, $\alpha_{H,a(s)}$ is the parameters associated with the latent ability, and $e_{H,a(s)}$ represents an idiosyncratic error term such that $e_{H,a(s)} \perp (\theta, X_H)$ for any $a(s)(=1,\ldots,\overline{A})$ and $s(=1,\ldots,\overline{S})$.

4.4 The Model for Employment

Let $I_{E,a(s)}$ denote the net benefit associated with the alternative of having an employment (versus the alternatives of unemployment or out of the labor force) given the schooling level *s* and the accumulated experience *a(s)*. As in the previous cases, we assume a linear-in-the-parameters specification for $I_{E,a(s)}$:

$$I_{E,a(s)} = \varphi_{E,a(s)} Gender + \beta_{E,a(s)} X_E + \alpha_{E,a(s)} \theta + e_{E,a(s)} \text{ for } s = 1,\ldots,\overline{S},\ a(s) = 1,\ldots,\overline{A} \quad (5)$$

where $\varphi_{E,a(s)}$, $\beta_{E,a(s)}$, X_E, $\alpha_{E,a(s)}$, and $e_{E,a(s)}$ are defined as before. Finally, the error term is such that $e_{E,a(s)} \perp (\theta, X_E)$ for any $a(s)(=1,\ldots,\overline{A})$ and $s(=1,\ldots,\overline{S})$.

We use (5) to model the employment decisions observed in the data. Specifically, if we let $D_{E,a(s)}$ denote a binary variable such that is equal to 1 if the individual is employed and 0 otherwise, we estimate a binary model assuming that $D_{E,a(s)} = 1\lfloor I_{E,a(s)} > 0 \rfloor$ where 1[.] is (again) the indicator function.

4.5 Schooling Performance: The Measurement System

The identification of the model can be established using the arguments developed in Carneiro, Hansen, and Heckman (2003) and Hansen, Heckman, and Mullen (2004). The identification strategy assumes the existence of a set of measurements. As explained in the next section, these measurements are associated to the individual's schooling performance.

Let T_i (i=1,…,n_C) denote the *i*-th measure. We distinguish the unobserved ability from the observed measure T_i. This is important since T_i is likely to depend on the characteristics of school as well as on the family background of the individuals by the time of the test. Thus, if X_T denote these characteristics, we have

$$T_i = \beta_{T_i} X_T + \alpha_{T_i} \theta + e_{T_i} \quad \text{for } i = 1,\ldots,n_C$$

where $e_{T_i} \perp (\theta, X_T)$ and $e_{T_i} \perp e_{T_j}$ for any $i, j \in \{1,\ldots,n_C\}$ such that *i≠j*.

Since there are no intrinsic units for the latent ability, we need to normalize one of the loadings in the system to unity to set the scale of the latent ability. Therefore, for some T_i (i=1,…,n_C), we set α_{T_i} =1.

Notice that our assumptions imply that conditional on observables (variables contained in X), the dependence across all measurements, choices and outcomes come through the unobserved heterogeneity (θ). Notice that if θ were observed, we could use a matching type of approach to control for this dependence (selection). Instead, we estimate the distribution of the unobserved ability and then control for the dependence. Finally, we assume that θ measures the same thing for males and females.

4.6 Implementing the Model

The model with unobserved heterogeneity has the following ingredients: the schooling decision problem, the linear models for hourly wages and monthly hours worked (by schooling level s and experience level $a(s)$), the models for employment (by schooling level s and experience level $a(s)$), the model for accumulated experience (by schooling level), and finally, the system of measurements or school achievement. Unobserved heterogeneity appears as determinant of each of these components. In this paper we assume that θ is distributed according to a two-component mixture of normals. Formally,

$$\theta \sim p_1 N\left(\mu_1, \sum\nolimits_1^2\right) + (1 - p_1) N\left(\mu_1, \sum\nolimits_2^2\right).$$

with this assumption we allow a flexible functional form for the unobserved heterogeneity.

Following the empirical strategy utilized in Section 3, we estimate the schooling choice model and the experience models using multinomial probit models. Then, we implicitly assume that the idiosyncratic shocks in the equations describing the net utilities are assumed to be jointly normally distributed. The four schooling levels study used here are: primary school, secondary school (or high school), some tertiary education (or some college graduates), and complete tertiary education (or college graduates). For accumulated experience we use three categories: less than 10 years of experience, between 10 and 15 years of experience, and more than 15 years of experience.

In estimating the model, and since there is no sequential decision process, we use the schooling and experience level reported at the time of the interview.[32]

For the models of wages and hours worked we use the information for the month previous to the interview. The same applies in the case of employment status. This is consistent with what we use in Section 3.

The measurement system uses the following variables: Average Grade during Secondary Education, Repeated Grade during Primary Education and Repeated Grade during Secondary Education.

We normalize the mean of the factor to zero, and we normalize the loading to be equal to one in the equation for the Average Grade during Secondary Education

Tables 8A and 8B display the variables used in the empirical implementation of the model, as well as the normalization assuring the identification of the model. The model is estimated using Markov Chain Markov Chain Monte Carlo Methods (MCMC). See Appendix A for a formal discussion of the method used in this paper.

4.7 Main Results

Table 9 presents the gender gaps in hourly wages obtained from the model with unobserved heterogeneity. The estimated gaps are in general sizeable and statistically significant. We do not observe clear patterns either by schooling and/or experience levels, although we consistently estimated the largest gender gaps among college graduates (regardless of the experience level considered). In this group we estimate that males make between 36% and 38% more per hour than females. These numbers are larger than those presented in Section 3. But Table 9 also presents a range for the gender gap in wages which goes from -6% (but non significant) for high school dropouts reporting less than 10 years of experience to 38% for college graduates with between 10 and 15 years of experience. Importantly, in only two cases we estimate a gender gap below 15%.

[32] In the case of experience, we use the retrospective information provided by the respondent (labor history). The labor history is reported from age 15 or since 1980 depending on the year the individual became 15 years old. For details see Section 2.

Therefore, our evidence indicates the existence of wage differentials that cannot be explained by observed or unobserved characteristics.

As in the case of wages, the results obtained for hours worked show a range of values for the gender gaps. These are presented in Table 10. We observe that the point estimates are between -6% (high school dropouts with less than 10 years of experience) and 18% (high school dropouts with between 10 and 15 years of experience). In this case however, less than a half of the estimates are statistically significant. For example, among high school graduates and college graduates we do not find significant gender differences. This is consistent with the evidence presented in Section 3, although the numbers in Table 10 show a broader picture of the gender gaps (if any) in hours worked.

Table 11 presents the results for employment. Two are the main results here. First, we observe, in general, a reduction in the estimated gap when we move from low to high experience levels (the only exception is observed among high school graduates). Second, the results suggest that schooling also helps to reduce the estimated gaps (there are only two exceptions in Table 11). In fact, among college graduates the estimated coefficients are -0.12 and -0.23 for experience levels "between 10 and 15 years" and "more than 15 years", respectively,[33,34] so the gap favor females in this case. However, as in the case of hours worked, only few estimates are statistically significant, and when significant, they are usually associated with low schooling and experience levels.

Table 12 presents the results obtained for the four multinomial choice models used to study accumulated experience. The evidence in Table 12 shows how the gender gap reduces with schooling. Specifically, the significant gender differences estimated for high school dropouts and high school graduates are 100% larger than the ones obtained among individuals with some college. Interestingly, among college graduates we do not find significant differences between genders.

Our analysis of gender gaps in variables associated with the labor market leads us to conclude that (1) there are differences between males and females that cannot be explained with observable or unobservable characteristics, and that, in general, (2) these differences are larger among individuals reporting low schooling level and they almost vanish among the more educated individuals.[35]

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[33] For the group of individuals reporting more than 15 years of experience and a college degree, the gender dummy perfectly predicts the labor status: the 29 women in this category reported a job during the week previous to the interview.
[34] These coefficients are the point estimates of the parameters associated with the gender dummy variable, so they need to be interpreted cautiously since they do not represent the marginal effects.
[35] The only exception to this point, and an important one, comes from the analysis of hourly wages.

The model also allows us to analyze the gender differences in schooling attainment and schooling achievement. It is worth recalling that the evidence presented in Section 3 already suggested that females outperform males in these two dimensions (see Tables 6 and 7). Table 13 and 14 repeat that analysis but now incorporating unobserved heterogeneity (latent ability).

Table 13 presents the gender gaps in schooling decisions. The results show (again) that females are more likely than males to reach higher schooling levels. When compared with those in Table 6, we see that the effects are now larger. Something similar occurs in the case of "repeating a grade during primary school", "repeating a grade during secondary school", and "average grades during high school". The results are shown in Table 14. The evidence in this table suggests that females outperform males, that the differences are statistically significant and that they are larger than the ones presented in Table 7. Specifically, when comparing the estimated gender gaps across tables we obtain 18% (0.26 versus 0.22) and 41% (0.17 versus 0.12) increments in the gender coefficient associated with "repeating a grade in primary school" and "repeating a grade in secondary school", respectively. In the case of "average grade during secondary school" we obtain an increment of 6.4% in the gender gap (0.33 versus 0.31).

5 Can Unobserved Heterogeneity Explain the Gender Gaps in the Labor Market?

From the evidence presented in this paper we must conclude that this is still an open question. Our results do indicate that, after controlling for unobserved heterogeneity, there are non significant gender differences in a variety of labor market variables among educated individuals (e.g., hours worked, accumulated experience, employment), but we still find gender differences among the other schooling groups. These differences can in principle be interpreted as "pure" discrimination. However, this interpretation requires several qualifications.

First, our empirical strategy assumes that a one dimensional model of unobserved heterogeneity is sufficient to capture and control for selection (endogeneity) across different margins (decisions). Nevertheless, previous studies have shown the existence of at least two underlying sources of unobserved heterogeneity when explaining labor market outcomes and social behavior.[36] In this context, our one-

[36] See Heckman, Stixrud, and Urzua, 2006; Urzua, 2006; Cunha, Heckman and Navarro, 2004.

dimensional model might be only partially capturing the unobserved heterogeneity in the data. The consequences of incorporating additional sources of essential heterogeneity on our results are hard to predict. Thus, in principle, we cannot discard the possibility that what we interpret as "unexplained gaps" in the one dimensional case, can be in fact "explained" by, for example, heterogeneity in other unobserved traits (e.g. noncognitive abilities) or preferences (e.g. preferences for leisure).[37]

Second, and following up on the previous point, it is interesting to notice that in our results the coefficients associated with what we identify as unobserved heterogeneity are not always significant. The strongest effect of unobserved heterogeneity are obtained for the schooling variables (Tables 13 and 14), and accumulated experience (Table 12). Although the effects are sizeable for the other outcomes, they are usually non-statistically significant. This suggests that our source of unobserved heterogeneity is more closely related to scholastic ability[38] which apparently is not significantly *valued* in the Chilean labor market after schooling and experience levels are taken into account. Nevertheless, there might be other sources of unobserved heterogeneity that are in fact *priced* in the labor market. This again illustrates the potential benefits of extending the model to multiple dimensions of unobserved heterogeneity

A different consideration regarding the robustness and interpretation of our results can be made by noticing that we implement the model by assuming the existence of a single distribution of unobserved heterogeneity in the sample. The consequences of allowing gender-specific distributions on our previous results are (again) hard to predict, but we believe that the complications of such extension would most likely dominate any potential new insights. This since the identification of gender-specific distribution has additional complications and it relies on even stronger assumptions that the one already made.[39] Besides, from an

[37] It is worth noting that the assumption of a single source of unobserved heterogeneity can be relaxed depending on the availability of more comprehensive information at the individual level. These needs for better and more comprehensive information come from the identification argument of the models. Recall that the source of unobserved heterogeneity in this paper is identified using the schooling achievement variable. In order to identify additional sources of heterogeneity we would need additional variables in the measurement system. The availability of information on personality traits, IQ tests, or time preferences could allow the identification and estimation of more general models of unobserved heterogeneity.

[38] Before we interpret the source unobserved heterogeneity as a combination of cognitive and noncognitive abilities.

[39] Specifically, even though we can assure the identification of gender-specific variance/covariance matrices, the identification of gender-specific mean differences in the distribution of unobserved heterogeneity would require the existence of at least one discrimination free variable. The selection and existence of such variable(s) is non trivial is arguably as well. See Urzua (2006) for details.

intuitive point of view, we do not find a priori deep reasons to believe that there are gender differences in the distributions of unobserved heterogeneity. It is because of this remarks that the estimation of gender-specific distribution is left for future research.

6 Conclusions

In this paper we present a comprehensive analysis of the gender gaps in a variety of labor market outcomes for Chile. The analysis is carried out using two different approaches. The first approach follows the literature by estimating linear and nonlinear models of a variety of variables on different observable controls and the gender dummy. This approach does not pay attention to potential selection problems (endogeneity). The second approach is more general. It allows for the presence of individuals' unobserved heterogeneity that is assumed to be the cause of the endogeneity problems in the conventional approach.

Our main results are robust across the approaches. They suggest the existence of gender gaps in labor market variables that cannot be explained by observable or unobservable characteristics or by underlying selection mechanisms generating endogeneity. Nevertheless, the findings from the model with unobserved heterogeneity indicate that the gender gaps critically depend on the schooling level of the individuals considered in the analysis. This is particular important among college graduates. For this group, the gender differences are in general non-significant.

The evidence also demonstrates that females outperform males in schooling achievement and schooling performance. This is observed regardless of the approach, but we find the stronger effects in the model with unobserved heterogeneity. These gender differences favoring women represent an argument against the conventional idea that labor market differences can be interpreted as the result of differences in the human capital between genders. Obviously, this conclusion assumes that the utilized variables are good proxies of the actual human capital accumulated by the individuals.

Overall, the estimates in this paper could lead us to conclude that women are effectively discriminated in the labor market with the largest gender gaps observed among the less educated people. However, we prefer to interpret our results cautiously. We believe that the availability of better data and the estimation of even more general models than the one considered here could indeed explain some of the unexplained estimated gender gaps.

References

Carneiro, P., K. Hansen, and J. Heckman (2003). Estimating distributions of treatment effects with an application to the returns to schooling and measurement of the effects of uncertainty on college choice. *International Economic Review* 44 (2), 361—422. 2001 Lawrence R. Klein Lecture.

Cunha, F., J. Heckman, and S. Navarro. Separating Uncertainty from Heterogeneity in Life Cycle Earnings. The 2004 Hicks Lecture, Oxford Economic Papers 57(191-261), 1-72

Hansen, K., J. Heckman, and K. Mullen (2004). The effect of schooling and ability on achievement test scores. *Journal of Econometrics* 121 (1-2), 39—98.

Heckman, J. (1974). Shadow prices, market wages, and labor supply. *Econometrica* 42(4), 679.

Heckman, J. (1981). Statistical models for discrete panel data. In C. Manski and D. Mc-Fadden (Eds.), *Structural Analysis of Discrete Data with Econometric Applications*, pp. 114—178. Cambridge, MA: MIT Press.

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(3).

Urzua, S. (2006). Racial Labor Market Gaps: The Role of Abilities and Schooling Choices. Working paper, University of Chicago.

6 Appendix A: The Computation of the Model

We use the Markov Chain Monte Carlo (MCMC) method to estimate the model introduced in Section 3. This appendix illustrates the algorithm using a simplified version of the model. The model used here is a two-sector Roy economy. Formally, let I denote the net utility associated with the choice problem of selecting between to sectors. Let Y_0 and Y_1 denote the associated potential outcomes. Thus,

$$\begin{aligned} Y_1 &= X_1\beta_1 + \varepsilon_1 \\ Y_0 &= X_0\beta_0 + \varepsilon_0 \\ D &= 1(I > 0) \end{aligned}$$

with $I = Z\gamma + V$. In addition, assume that

$$\begin{aligned} V &= \theta\alpha_V + U_V \\ \varepsilon_1 &= \theta\alpha_1 + U_1 \\ \varepsilon_0 &= \theta\alpha_0 + U_0 \end{aligned}$$

$U_1 \perp\!\!\!\perp U_0 \perp\!\!\!\perp U_V$, and $f \perp\!\!\!\perp (U_0, U_1, U_V)$, and

$$\begin{aligned} U_1 &\sim N(0, \sigma^2_{U_1}) \\ U_0 &\sim N(0, \sigma^2_{U_0}) \\ U_V &\sim N(0, \sigma^2_{U_V}) \end{aligned}$$

Following the identification strategy discussed in Section 3.4, we assume the existence of a set of measurements

$$T_h = Q_h\eta_h + \theta\delta_h + U_{T_h}$$

where $U_{T_h} \sim N(0, \sigma^2_{U_{T_h}})$ with $h = 1, ..., H$.

Finally, the unobserved factor is assumed to be distributed according to a mixture of K-normal distributions, i.e.

$$\theta \sim MN\left(\{\mu_k\}_{k=1}^K, \{\Sigma_{fk}\}_{k=1}^K, \{p_k\}_{k=1}^K\right)$$

such that $E(\theta) = 0$.

The likelihood function of the model is given by:

$$\begin{aligned}\Gamma(Y,T,D;\Theta) &= \prod_{j=1}^{N}\int\left[\prod_{h=1}^{H}\frac{1}{\sqrt{2\pi}\sigma^2_{U_{T_h}}}\exp\left(-\frac{1}{2\sigma^2_{U_{T_h}}}(T_{h,j}-Q_{h,j}\eta_h-\theta_j\delta_h)^2\right)\right]\\ &\left[\frac{1}{\sqrt{2\pi}\sigma_{U_1}}\exp\left(-\frac{1}{2\sigma^2_{U_1}}(Y_{1,j}-X_j\beta_1-\theta_j\alpha_1)^2\right)\Phi\left(-Z_j\gamma-\theta_j\alpha_V\right)\right]^{D_i}\\ &\left[\frac{1}{\sqrt{2\pi}\sigma_{U_0}}\exp\left(-\frac{1}{2\sigma^2_{u0}}(Y_{0,j}-X_j\beta_0-\theta_j\alpha_0)^2\right)(1-\Phi\left(-Z_j\gamma-\theta_j\alpha_V\right))\right]^{1-D_i}dF(\theta_j).\end{aligned}$$

6.1 The Gibbs Sampler

We start by specifying the priors. For the parameters in the models for wages $\left(\beta_j,\alpha_j,1/\sigma^2_{U_j}\right)$:

$$\begin{aligned}\beta_j &\sim N\left(\beta^0_j,\sigma^0_{\beta_j}I\right)\\ \alpha_j &\sim N\left(\alpha^0_j,\sigma^0_{\alpha_j}I\right)\\ 1/\sigma^2_{U_j} &\sim Gamma\left(a_{U_j},b_{U_j}\right).\end{aligned}$$

For the parameters in the models for test scores $\left(\eta_h,\delta_h,1/\sigma^2_{U_{Th}}\right)$:

$$\begin{aligned}\eta_h &\sim N\left(\eta^0_h,\sigma^0_{\eta_h}I\right)\\ \delta_h &\sim N\left(\delta^0_h,\sigma^0_{\delta_h}I\right)\\ 1/\sigma^2_{U_{T_h}} &\sim Gamma\left(a_{U_{T_h}},b_{U_{T_h}}\right).\end{aligned}$$

For the parameters in the model for the latent variable (γ,α_V) :

$$\begin{aligned}\gamma &\sim N\left(\gamma^0,\sigma^0_\gamma I\right)\\ \alpha_V &\sim N\left(\alpha^0_V,\sigma^0_{\alpha_V}I\right).\end{aligned}$$

For the parameters in the factor's distribution $\left(\{\mu_k\}^K_{k=1},\{\Sigma_{\theta,k}\}^K_{k=1},\{p_k\}^K_{k=1}\right)$:

$$p\sim Dirichlet\left(a_1,...,a_K\right)$$

$$\Sigma_{\theta,k}\sim Gamma\left(v^0_k,V^0_k\right)$$

$$\mu_k\sim N\left(\mu^0_k,\sigma^0_{\mu_k}\right).$$

Notice that in what follows we denote $\Gamma_{\theta,l} = \Sigma_{\theta,l}^{-1}$, i.e $\Gamma_{\theta,l}$ denotes the precision for the l component.

Let $\lambda = (\alpha, \beta, \tau, \gamma, \eta, \theta, \Sigma)$. Using the block structure of the model we can derive the formulae for the conditional posteriors:

For wages:

$$f(\beta_j/\alpha_j, \tau_{U_j}, \theta, Y, D) \propto \exp\left\{-\frac{\tau_{U_j}}{2}\left(\sum_{i:D=j}(Y_i - X_i\beta_j - \alpha_j\theta_i)^2\right) - \frac{\sigma^0_{\beta_j}}{2}\left(\beta_j - \beta^0_j\right)'\left(\beta_j - \beta^0_j\right)\right\} \quad \text{for } i = 0, 1$$

consequently,

$$\beta_j \sim N\left(\left(\tau_{U_j}\sum_{i:D=j}X_iX_i' + \tau^0_{\beta_j}I\right)^{-1}\left(\tau_{U_j}\sum_{i:D=j}X_i(Y_i - \alpha_j\theta_i) + \tau^0_{\beta_j}I\beta^0_j\right), \left(\tau_{U_j}\sum_{i:D=j}X_iX_i' + \tau^0_{\beta_j}I\right)^{-1}\right) \tag{4}$$

Similarly for α_j,

$$\alpha_j \sim N\left(\left(\tau_{U_j}\sum_{i:D=j}\theta_i^2 + \tau^0_{\alpha_j}\right)^{-1}\left(\tau_{U_j}\sum_{i:D=j}\theta_i(Y_i - X_i\beta_j) + \tau^0_{\alpha_j}\alpha^0_j\right), \left(\tau_{U_j}\sum_{i:D=j}\theta_i^2 + \tau^0_{\alpha_j}\right)^{-1}\right). \tag{5}$$

For test scores:

Following the same logic as in the previous case, it is straightforward to obtain that:

$$\eta_h \sim N\left(\left(\tau_{U_{T_h}}\sum_{i=1}^{N}Q_iQ_i' + \tau^0_{\eta_h}I\right)^{-1}\left(\tau_{U_{T_h}}\sum_{i=1}^{N}Q_i(T_{h,i} - \delta_h\theta_i) + \tau^0_{\eta_h}I\theta^0_h\right), \left(\tau_{U_{T_h}}\sum_{i=1}^{N}Q_iQ_i' + \tau^0_{\eta_h}I\right)^{-1}\right) \tag{6}$$

and

$$\delta_h \sim N\left(\left(\tau_{U_{T_h}}\sum_{i=1}^{N}\theta_i^2 + \tau^0_{\delta_h}\right)^{-1}\left(\tau_{U_{T_h}}\sum_{i=1}^{N}\theta_i(T_{h,i} - \eta_hQ_i) + \tau^0_{\delta_h}\delta^0_h\right), \left(\tau_{U_{T_h}}\sum_{i=1}^{N}\theta_i^2 + \tau^0_{\delta_h}\right)^{-1}\right). \tag{7}$$

For probit:

We need a completion for D. Let D^* be the latent variable. Thus,

$$\begin{aligned} f(\gamma, \alpha_V, D^*/D) &= f(D/\alpha_V, \gamma, D^*) f(D^*/\alpha_V, \gamma) f(\gamma) f(\alpha_V) \\ &= \left[\left(\frac{1}{\sigma^0_{\alpha_V}}\right)^{Dim(\alpha_V)/2} \exp\left(-\frac{\sigma^0_{\alpha_V}}{2}\left(\alpha_V - \alpha^0_V\right)\left(\alpha_V - \alpha^0_V\right)'\right)\right] \\ &\times \left[\left(\frac{1}{\sigma^0_\gamma}\right)^{Dim(\gamma)/2} \exp\left(-\frac{\sigma^0_\gamma}{2}\left(\gamma - \gamma^0\right)\left(\gamma - \gamma^0\right)'\right)\right] \\ &\times \prod_{i=1}^{N} \Big\{\left[1(D^*_i > 0)\phi\left(D^*_i - Z_i\gamma - \alpha_V\theta_i\right)\right]^{D_i} \\ &\times \left[1(D^*_i < 0)\phi\left(D^*_i - Z_i\gamma - \alpha_V\theta_i\right)\right]^{1-D_i}\Big\} \end{aligned}$$

Now,

$$\begin{aligned} f(\gamma/\alpha_V, \theta, D^*, D, Z) &\propto \prod_{i=1}^{N} \phi\left(D^*_i - z_i\gamma - \alpha_V\theta_i\right) \\ &\propto \exp\left\{-\frac{1}{2}\sum_{I=1}^{N}\left(D^*_i - z_i\gamma - \alpha_V\theta_i\right)^2 - \frac{\sigma^0_\gamma}{2}\left(\gamma - \gamma^0\right)\left(\gamma - \gamma^0\right)'\right\} \end{aligned}$$

Consequently,

$$\gamma \sim N\left(\left(z'z + \tau^0_\gamma I\right)^{-1}\left(z'\left(D^* - \alpha_V\theta\right) + \tau^0_\gamma I\gamma^0\right), \left(z'z + \tau^0_\gamma I\right)^{-1}\right) \qquad (8)$$

Using the same logic as in (5) we obtain:

$$\alpha_V \sim N\left(\left(\sum_{i=1}^{N}\theta_i^2 + \tau^0_{\alpha_V}\right)^{-1}\left(Z'\left(D^* - \alpha_V\theta\right) + \tau^0_{\alpha_V}\alpha^0_V\right), \left(\sum_{i=1}^{N}\theta_i^2 + \tau^0_{\alpha_V}\right)^{-1}\right). \qquad (9)$$

Finally,

$$f(D^*_i/\alpha_V, \theta, \gamma, D) \propto \left[1(D^*_i > 0)\phi\left(D^*_i - Z_i\gamma - \alpha_V\theta_i\right)\right]^{D_i}\left[1(D^*_i < 0)\phi\left(D^*_i - Z_i\gamma - \alpha_V\theta_i\right)\right]^{1-D_i}$$

Therefore, we sample D^*_i from:

$$D^*_i = \begin{cases} TN_{[0,\infty)}\left(Z_i\gamma + \alpha_V\theta_i, 1\right) \text{ if } D_i = 1 \\ TN_{(-\infty,0]}\left(Z_i\gamma + \alpha_V\theta_i, 1\right) \text{ if } D_i = 0 \end{cases} \qquad (10)$$

Precisions:

The posterior distributions for the precisions are:

$$\tau_{U_j} \sim G\left(\frac{\sum_{i:D=j} 1}{2} + a_{U_j}, \left(\frac{1}{2}\sum_{i:D=j}\left(Y_i - X_i\beta_j - \alpha_j\theta_i\right)^2\right) + b_{U_j}\right) \quad \text{for } i = 0,1 \qquad (11)$$

$$\tau_{U_{T_h}} \sim G\left(\frac{N}{2} + a_{U_{T_h}}, \left(\frac{1}{2}\sum_{j=1}^{N}\left(T_{h,i} - Q_i\eta_h - \delta_h\theta_i\right)^2\right) + b_{U_{T_h}}\right) \quad \text{for } h = 1,..,H. \qquad (12)$$

Factor's Distribution:

Since we restrict the mean to be zero: $\mu_L = -\sum_{l=1}^{L-1}\frac{p_l}{p_L}\mu_l$, we have that

$$\exp\left(-\frac{\tau_\mu^0}{2}\left(\mu_1-\mu^0\right)\left(\mu_1-\mu^0\right)' - \frac{1}{2}\sum_{i,1}\left(\theta_i-\mu_1\right)\Gamma_{\theta,1}\left(\theta_i-\mu_1\right)'\right)$$

$$\vdots$$

$$\times\exp\left(-\frac{\tau_\mu^0}{2}\left(-\sum_{l=1}^{L-1}\frac{p_l}{p_L}\mu_l-\mu^0\right)\left(-\sum_{l=1}^{L-1}\frac{p_l}{p_L}\mu_l-\mu^0\right)' - \frac{1}{2}\sum_{i,L}\left(\theta_i+\sum_{l=1}^{L-1}\frac{p_l}{p_L}\mu_l\right)\Gamma_{\theta,L}\left(\theta_i+\sum_{l=1}^{L-1}\frac{p_l}{p_L}\mu_l\right)'\right)$$

$$= \exp\left(-\frac{\tau_\mu^0}{2}\left(\mu_1-\mu^0\right)\left(\mu_1-\mu^0\right)' - \frac{1}{2}\sum_{i,1}\left(\theta_i-\mu_1\right)\Gamma_{f,1}\left(\theta_i-\mu_1\right)'\right)$$

$$\vdots$$

$$\times\exp\left(\begin{array}{c} -\frac{\tau_\mu^0}{2}\left(\frac{p_1}{p_L}\right)^2\left(\mu_1-\left(-\sum_{l=2}^{L-1}\frac{p_l}{p_1}\mu_l-\frac{p_L}{p_1}\mu^0\right)\right)\left(\mu_1-\left(-\sum_{l=2}^{L-1}\frac{p_l}{p_1}\mu_l-\frac{p_L}{p_1}\mu^0\right)\right)' \\ -\frac{1}{2}\left(\frac{p_1}{p_L}\right)^2\sum_{i,L}\left(\mu_1-\left(-\frac{p_L}{p_1}\theta_{L,i}-\sum_{l=2}^{L-1}\frac{p_l}{p_1}\mu_l\right)\right)\Gamma_{\theta,L}\left(\mu_1-\left(-\frac{p_L}{p_1}\theta_{L,i}-\sum_{l=2}^{L-1}\frac{p_l}{p_1}\mu_l\right)\right)' \end{array}\right)$$

thus,

$$\mu_1 \sim N \left(\begin{array}{c} \left(\tau_\mu^0 + N_1\Gamma_{\theta,1} + \left(\frac{p_1}{p_L}\right)^2 \left(\tau_\mu^0 + N_L\Gamma_{\theta,L}\right)\right)^{-1} \left(\begin{array}{c} \tau_\mu^0\mu^0 + \Gamma_{\theta,1}\sum_{i=1,1\theta i} \\ + \left(\frac{p_1}{p_L}\right)^2 \tau_\mu^0 \left(-\sum_{l=2}^{L-1} \frac{p_l}{p_1}\mu_l - \frac{p_L}{p_1}\mu^0\right) \\ + \left(\frac{p_1}{p_L}\right)^2 \Gamma_{\theta,L}\sum_{i=1,L}\left(-\frac{p_L}{p_1}\theta_i - \sum_{l=2}^{L-1}\frac{p_l}{p_1}\mu_l\right) \end{array} \right), \\ \left(\tau_\mu^0 + \Gamma_{\theta,l} + \tau_\mu^0\left(\frac{p_1}{p_L}\right)^2 + \left(\frac{p_1}{p_L}\right)^2\Gamma_{\theta,L}\right)^{-1} \end{array} \right)$$

For the probabilities,

$$\Pr(p|) \propto \frac{1}{B(\alpha)}\prod_{l=1}^{L} p_l^{\alpha_l+N_l-1}$$

so,

$$p \sim D\left(\alpha_1 + N_1, ..., \alpha_L + N_L\right).$$

For the group indicator

$$z_i \sim MN\left(\frac{p_1\phi\left(\theta_i, \mu_1, \Gamma_{\theta,1}\right)}{\sum_l p_l\phi\left(\theta_i, \mu_l, \Gamma_{\theta,l}\right)}, ..., \frac{p_L\phi\left(\theta_i, \mu_L, \Gamma_{\theta,L}\right)}{\sum_l p_l\phi\left(\theta_i, \mu_l, \Gamma_{\theta,l}\right)}\right)$$

Following the same argument as in the case of the other precisions, we have that the posterior distribution for the precisions $\Gamma_{\theta,l}$ follows a Gamma distribution.

Finally the *posterior for the factor*:

$$\begin{aligned} \Pr(\theta_i/\lambda, Y_i, T_i, D_i &= 1) \propto \exp\left(-\frac{\tau_{U_1}}{2}(Y_i^1 - X_i\beta_1 - \theta_i\alpha_1)^2\right) \\ &\times \exp\left(-\frac{1}{2}\left(D_i^* - Z_i\gamma - \alpha_V\theta_i\right)^2\right) \\ &\times \exp\left(-\sum_{h=1}^{H}\frac{\tau_{U_{Th}}}{2}(T_{i,h} - Q_{i,k}\eta_h - \theta_i\delta_h)^2\right) \\ &\times \exp\left(-\frac{1}{2}\theta_i^2\Gamma_\theta\right) \\ &= \exp\left(\begin{array}{c} -\frac{\tau_{U_1}}{2}(Y_i^1 - X_i\beta_1 - \theta_i\alpha_1)^2 - \frac{1}{2}\left(D_i^* - Z_i\gamma - \alpha_V\theta_i\right)^2 \\ -\sum_{h=1}^{H}\left(\frac{\tau_{U_{T_h}}}{2}(T_{i,h} - Q_{i,h}\eta_h - \theta_i\delta_h)^2\right) - \frac{1}{2}\theta_i^2\Gamma_\theta \end{array} \right) \end{aligned}$$

To simplify notation let $\theta_i^* = Y_i - X_i\beta_j$, $\theta_{i,k}^* = T_{i,k} - Q_{i,k}\theta_k, \theta_i^{***} = D_i^* - Z_i\gamma$. Then

$$\Pr(\theta_i/\lambda, Y_i, T_i, D_i = 1) \propto \exp\begin{pmatrix} -\frac{\tau_{U_1}}{2}(\theta_i^* - \theta_i\alpha_1)^2 - \frac{1}{2}\left(\theta_i^{***} - \alpha_V\theta_i\right)^2 \\ -\sum_{k=1}^{K}\left(\frac{\tau_{U_{T_k}}^{n/2}}{2}(\theta_{i,k}^* - \theta_i\delta_k)^2\right) - \frac{1}{2}\theta_i^2\Gamma_\theta \end{pmatrix}.$$

Notice that

$$\exp\left(-\frac{\tau_{U_1}}{2}(\theta_i^* - \theta_i\alpha_1)^2 - \frac{1}{2}\left(\theta_i^{***} - \alpha_V\theta_i\right)^2\right) \propto \exp\begin{pmatrix} -\frac{\tau_{U_1}}{2}\left(\theta_i - \overline{\theta}_i^*\right)'\alpha_1'\alpha_1\left(\theta_i - \overline{\theta}_i^*\right) \\ -\frac{1}{2}\left(\theta_i - \overline{\theta}_i^{**}\right)'\alpha_V'\alpha_V\left(\theta_i - \overline{\theta}_i^{**}\right) \end{pmatrix}$$

where $\overline{\theta}_i^* = (\alpha_1'\alpha_1)^{-1}(\alpha_1\theta_i^*)$ and $\overline{\theta}_i^{**} = (\alpha_V'\alpha_V)^{-1}(\alpha_V\theta_i^{**})$. Then,

$$\exp\left(-\frac{\tau_{U_1}}{2}(\theta_i^* - \theta_i\alpha_1)^2 - \frac{1}{2}\left(\theta_i^{***} - \alpha_V\theta_i\right)^2\right) \propto \exp\left(-\frac{1}{2}\left(\theta_i - \widetilde{\varrho}_i\right)'\widetilde{\varkappa}\left(\theta_i - \widetilde{\varrho}_i\right)\right)$$

where $\widetilde{\varrho}_i = (\tau_{U_1}\alpha_1'\alpha_1 + \alpha_V'\alpha_V)^{-1}\left(\tau_{U_1}\alpha_1'\alpha_1\overline{\theta}_i^* + \alpha_V'\alpha_V\overline{\theta}_i^{**}\right)$ and $\widetilde{\varkappa} = (\tau_{U_1}\alpha_1'\alpha_1 + \alpha_V'\alpha_V)$.

Repeating the same argument multiple times we get,

$$\Pr(\theta_i/\lambda, Y_i, T_i, D_i = 1) \sim N\left(\overline{\mu}_{\theta,i}, \overline{\Sigma}_\theta\right) \tag{13}$$

with

$$\overline{\mu}_{\theta,i} = \left(\tau_{U_1}\alpha_1'\alpha_1 + \alpha_V'\alpha_V + \sum_{h=1}^{H}\tau_{U_{T_h}}\delta_h'\delta_h + \Gamma_\theta\right)^{-1}\left(\tau_{U_1}\alpha_1'\alpha_1\overline{\theta}_i^* + \alpha_V'\alpha_V\overline{\theta}_i^{**} + \sum_{h=1}^{H}\tau_{U_{T_h}}\delta_h'\delta_h\overline{\theta}_{h,i}^*\right)$$

and

$$\overline{\Sigma}_\theta = \left(\tau_{U_1}\alpha_1'\alpha_1 + \alpha_V'\alpha_V + \sum_{h=1}^{H}\tau_{U_{T_h}}\delta_h'\delta_h + \Gamma_\theta\right)^{-1}$$

where $\overline{\theta}_{h,i}^* = (\delta_h'\delta_h)^{-1}(\delta_h^*\theta_{i,h})$.

Finally, the gibbs sampling procedure is:

1. Choose initial values for the parameters, and an arbitrary first draw for the factor. (I used $\theta^{(m)} \sim N(0,1)$)

For $m = 1, M$

1. Sample $D^*(j)^{(m)}$ for $j = 1, ..., N$ according to (10)

2. Sample $\theta(j)^{(m)}$ for $j = 1, ..., N$ according to (13)

3. Sample $\beta_i^{(m)}$ $(i = 1, 2)$ according to (4)

4. Sample $\alpha_i^{(m)}$ $(i = 1, 2)$ according to (5)

5. Sample $\gamma^{(m)}$ according to (8)

6. Sample $\alpha_V^{(m)}$ according to (9)

7. Sample $\tau_i^{(m)}$ $(i = 1, 2)$ according to (11)

8. Sample $\tau_T^{(m)}$ according to (12)

9. Sample $\tau_\theta^{(m)}$ according to the respective Gama distribution.

We iterate over m until converge.

The model introduced in Section 3 is simply a more general version of this two-sectors Roy model.

Table 1. Means of Schooling and Labor Market Outcomes by Gender
SPS02

Variable (Dummy=1 if Apply)	Females		Males	
	Mean	Std. Dev	Mean	Std. Dev
A. School Information				
Maximum Schooling Level = Primary Education	0.11	0.32	0.17	0.38
Maximum Schooling Level = Secondary Education	0.51	0.50	0.49	0.50
Maximum Schooling Level = Some Tertiary Education	0.26	0.44	0.24	0.43
Maximum Schooling Level = Complete Tertiary Education	0.11	0.31	0.10	0.30
Repeat a Grade in Primary School	0.22	0.41	0.30	0.46
Repeat a Grade in Secondary School	0.20	0.40	0.24	0.43
Average Grade in Secondary School [(a)]	0.16	0.98	-0.17	1.00
B. Labor Market Variables				
Monthly Earnings	215,266	214,323	285,140	360,046
Hours Worked per Week	43.41	11.74	48.17	9.81
Hourly Wage	1,292	1,257	1,636	4,649
Working During Last Month	0.59	0.49	0.82	0.39
Less than 10 years of Experience	0.56	0.50	0.25	0.43
Between 10 and 15 years of Experience	0.26	0.44	0.34	0.47
More than 15 years of Experience	0.18	0.39	0.41	0.49
Number of Observations		1,765		1,801

Note: The numbers presented in this table corresponds to the sample of individuals with ages between 28 and 40 years old at the time of the interview.

Table 2. The Gender Gap in Hourly Wages
SPS02

Variables	(A)	(B)	(C)	(D)
Male	**0.24**	**0.23**	**0.23**	**0.29**
	(0.03)	**(0.03)**	**(0.03)**	**(0.03)**
Schooling [a]				
Secondary Education	-	-	0.29	0.30
	-	-	(0.04)	(0.04)
Some Tertiary Education	-	-	0.49	0.50
	-	-	(0.04)	(0.05)
Complete Tertiary Education	-	-	0.90	0.92
	-	-	(0.06)	(0.06)
Experience [b]				
Between 10 and 15 years of Experience	-	0.04	0.05	0.14
	-	(0.03)	(0.03)	(0.03)
More than 10 years of Experience	-	0.04	0.10	0.19
	-	(0.03)	(0.03)	(0.04)
Residence [c]				
Central	-0.15	-0.15	-0.15	-0.15
	(0.04)	(0.04)	(0.04)	(0.04)
South	-0.04	-0.04	-0.05	-0.004
	(0.04)	(0.04)	(0.04)	(0.04)
Santiago	0.22	0.22	0.21	0.24
	(0.03)	(0.03)	(0.03)	(0.03)
Type of Job [d]				
Employer or Self-Worker	-0.13	-0.13	-0.10	-0.11
	(0.03)	(0.03)	(0.03)	(0.03)
Domestic Service	-0.08	-0.08	-0.04	-0.06
	(0.07)	(0.07)	(0.07)	(0.07)
Occupations [e]				
Professionals	0.09	0.10	-0.18	-0.17
	(0.07)	(0.07)	(0.07)	(0.07)
Technicians and associate professionals	-0.33	-0.33	-0.27	-0.25
	(0.07)	(0.07)	(0.07)	(0.07)
Clerks	-0.71	-0.72	-0.56	-0.53
	(0.07)	(0.07)	(0.06)	(0.06)
Service workers and shop and market sales workers	-1.08	-1.08	-0.84	-0.83
	(0.07)	(0.07)	(0.07)	(0.07)
Skilled agricultural and fishery workers	-1.35	-1.36	-0.96	-0.93
	(0.08)	(0.08)	(0.08)	(0.09)
Craft and related trades workers	-1.05	-1.05	-0.77	-0.74
	(0.06)	(0.06)	(0.06)	(0.06)
Plant and machine operators and assemblers	-1.11	-1.11	-0.85	-0.82
	(0.07)	(0.07)	(0.07)	(0.07)
Elementary occupations	-1.28	-1.28	-0.94	-0.91
	(0.07)	(0.07)	(0.07)	(0.07)
Constant	7.63	7.61	7.04	6.75
	(0.07)	(0.07)	(0.08)	(0.10)
Correction for Selection	No	No	No	Yes

Notes: (a) The baseline category is Primary Education; (b) The baseline category is Less than 10 years of experience; (c) The baseline category is North (I to III regions). Central represents IV-VII regions (including the XIII region), South represents VIII-XII regions; (d) The baseline category is Public and Private Employees; (e) The baseline category is Legislators, senior officials and managers. For each model Shooling corresponds to the declared schooling level for each individual in the sample. Specification (D) includes the same controls as (C) but is estimated including a correction for selection. The variables used in the first stage are number of children, mother's occupational situation, father's occupational situation, and whether or not the individual grew up in a poor household. Standard Errors are presented in parentheses.

Table 3. The Gender Gap in Monthly Hours Worked
SPS02

Variables	(A)	(B)	(C)	(D)
Male	**0.12**	**0.11**	**0.11**	**0.004**
	(0.02)	**(0.02)**	**(0.02)**	**(0.02)**
Schooling (a)				
Secondary Education	-	-	-0.01	-0.04
	-	-	(0.02)	(0.02)
Some Tertiary Education	-	-	0.02	-0.03
	-	-	(0.03)	(0.02)
Complete Tertiary Education	-	-	-0.03	-0.04
	-	-	(0.04)	(0.03)
Experience (b)				
Between 10 and 15 years of Experience	-	0.08	0.08	-0.07
	-	(0.02)	(0.02)	(0.02)
More than 10 years of Experience	-	0.08	0.08	-0.08
	-	(0.02)	(0.02)	(0.02)
Residence (c)				
Central	-0.002	-0.005	-0.01	0.02
	(0.03)	(0.03)	(0.03)	(0.03)
South	-0.05	-0.05	-0.05	-0.10
	(0.02)	(0.02)	(0.02)	(0.03)
Santiago	0.02	0.02	0.02	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)
Type of Job (d)				
Employer or Self-Worker	-0.20	-0.20	-0.20	-0.05
	(0.02)	(0.02)	(0.02)	(0.02)
Domestic Service	-0.11	-0.12	-0.12	0.01
	(0.04)	(0.04)	(0.04)	(0.03)
Occupations (e)				
Professionals	-0.30	-0.28	-0.27	-0.22
	(0.04)	(0.04)	(0.04)	(0.03)
Technicians and associate professionals	-0.24	-0.24	-0.25	-0.17
	(0.04)	(0.04)	(0.04)	(0.03)
Clerks	-0.18	-0.18	-0.19	-0.16
	(0.04)	(0.04)	(0.04)	(0.03)
Service workers and shop and market sales workers	-0.19	-0.19	-0.19	-0.11
	(0.04)	(0.04)	(0.04)	(0.03)
Skilled agricultural and fishery workers	-0.18	-0.20	-0.20	-0.16
	(0.05)	(0.05)	(0.05)	(0.04)
Craft and related trades workers	-0.16	-0.17	-0.18	-0.13
	(0.04)	(0.04)	(0.04)	(0.03)
Plant and machine operators and assemblers	-0.12	-0.13	-0.13	-0.06
	(0.04)	(0.04)	(0.04)	(0.03)
Elementary occupations	-0.24	-0.25	-0.25	-0.17
	(0.04)	(0.04)	(0.04)	(0.03)
Constant	3.95	3.91	3.92	4.21
	(0.04)	(0.04)	(0.05)	(0.04)
Correction for Selection	No	No	No	Yes

Notes: (a) The baseline category is Primary Education; (b) The baseline category is Less than 10 years of experience; (c) The baseline category is North (I to III regions). Central represents IV-VII regions (including the XIII region), South represents VIII-XII regions; (d) The baseline category is Public and Private Employees; (e) The baseline category is Legislators, senior officials and managers. For each model Shooling corresponds to the declared schooling level for each individual in the sample. Specification (D) includes the same controls as (C) but is estimated including a correction for selection. The variables used in the first stage are number of children, mother's occupational situation, father's occupational situation, and whether or not the individual grew up in a poor household. Standard Errors are presented in parentheses.

Table 4. The Gender Gap in Employment
SPS02

Variables	(A)		(B)		(C)	
	Coefficient	Marg. Effect	Coefficient	Marg. Effect	Coefficient	Marg. Effect
Male	**0.67**	**0.22**	**0.42**	**0.14**	**0.41**	**0.14**
	(0.05)	**(0.02)**	**(0.05)**	**(0.02)**	**(0.05)**	**(0.02)**
Background [(a)]						
Number of Children	-0.09	-0.03	-0.08	-0.03	-0.04	-0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Age	0.02	0.01	-0.03	-0.01	-0.04	-0.01
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Mother's Occupation	-0.05	-0.02	-0.03	-0.01	-0.06	-0.02
	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)
Father's Occupation	-0.27	-0.08	-0.21	-0.07	-0.13	-0.04
	(0.29)	(0.08)	(0.30)	(0.09)	(0.31)	(0.09)
Growing Up in Poverty	-0.24	-0.08	-0.27	-0.09	-0.14	-0.05
	(0.05)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)
Schooling [(b)]						
Secondary Education	-	-	-	-	0.26	0.09
	-	-	-	-	(0.07)	(0.02)
Some Tertiary Education	-	-	-	-	0.59	0.17
	-	-	-	-	(0.08)	(0.02)
Complete Tertiary Education	-	-	-	-	1.22	0.27
	-	-	-	-	(0.12)	(0.01)
Experience [(c)]						
Between 10 and 15 years of Experience	-	-	0.66	0.20	0.73	0.21
	-	-	(0.06)	(0.02)	(0.06)	(0.02)
More than 10 years of Experience	-	-	0.88	0.26	1.04	0.29
	-	-	(0.07)	(0.02)	(0.08)	(0.02)
Residence [(d)]						
Central	-0.08	-0.03	-0.09	-0.03	-0.06	-0.02
	(0.08)	(0.03)	(0.08)	(0.03)	(0.08)	(0.03)
South	0.22	0.07	0.24	0.08	0.24	0.08
	(0.08)	(0.03)	(0.08)	(0.03)	(0.08)	(0.03)
Santiago	0.24	0.08	0.24	0.08	0.18	0.06
	(0.06)	(0.02)	(0.06)	(0.02)	(0.06)	(0.02)
Constant	0.03	-	1.25	-	0.91	-
	(0.37)	-	(0.40)	-	(0.42)	-

Notes: (a) Mother's and Father's Education are dummy variables that take a value of one if the respective parent worked as asalaried and zero otherwise; (b) The baseline category is Primary Education; (c) The baseline category is Less than 10 years of experience; (d) The baseline category is North (I to III regions). Central represents IV-VII regions (including the XIII region), South represents VIII-XII regions. Standard Errors are presented in parentheses.

Table 5. The Gender Gap in Accumulated Experience
SPS02

Variables [b]	Less Than 10 Years [a]		Between 10 and 15 Years [a]		More than 15 Years [a]
	Coefficient	Marg. Effect	Coefficient	Marg. Effect	Marg. Effect
Male	**1.11**	**-0.40**	**1.92**	**0.11**	**0.29**
	(0.07)	**(0.02)**	**(0.09)**	**(0.02)**	**(0.02)**
Secondary Education	0.26	-0.04	-0.08	0.09	-0.04
	(0.11)	(0.03)	(0.12)	(0.03)	(0.02)
Some College	0.08	0.04	-0.61	0.08	-0.13
	(0.13)	(0.04)	(0.14)	(0.03)	(0.02)
College Graduates	-0.07	0.11	-1.16	0.07	-0.18
	(0.16)	(0.04)	(0.19)	(0.04)	(0.02)
Mother's Years of Schooling	-0.01	0.002	0.00	-0.002	-0.0003
	(0.01)	(0.003)	(0.01)	(0.003)	(0.003)
Father's Years of Schooling	-0.02	0.01	-0.04	-0.003	-0.01
	(0.01)	(0.003)	(0.01)	(0.003)	(0.003)
Growing Up in Poverty	-0.05	0.003	0.06	-0.02	0.02
	(0.08)	(0.02)	(0.09)	(0.02)	(0.02)
Growing Up in Broken Home	-0.15	0.01	0.16	-0.06	0.05
	(0.17)	(0.05)	(0.21)	(0.04)	(0.03)
Age	0.11	-0.07	0.42	-0.01	0.08
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Constant	-4.10		-15.07		
	(0.40)		(0.55)		

Notes: (a) The experience levels correspond to the accumulated experience declared during the interview. Post-secondary education includes includes technical education (complete and incomplete). (b) The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete).

Table 6. The Gender Gap in Schooling Decisions
SPS02

Variables	Primary School		Secondary School		Some Post-Secondary Education		College Graduates
	Coefficient	Marg. Effect	Coefficient	Marg. Effect	Coefficient	Marg. Effect	Marg. Effect
Male	**-0.30**	**0.04**	**-0.33**	**-0.02**	**-0.30**	**-0.02**	**-0.004**
	(0.08)	**(0.01)**	**(0.09)**	**(0.02)**	**(0.10)**	**(0.02)**	**(0.01)**
Mother's Years of Schooling	0.08	-0.02	0.15	-0.01	0.17	0.02	0.01
	(0.02)	(0.00)	(0.02)	(0.00)	(0.02)	(0.00)	(0.002)
Father's Years of Schooling	0.05	-0.01	0.13	-0.02	0.16	0.02	0.01
	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)	(0.00)	(0.002)
Growing Up in Poverty	-0.59	0.11	-0.84	0.00	-0.84	-0.08	-0.03
	(0.08)	(0.01)	(0.09)	(0.02)	(0.11)	(0.02)	(0.01)
Growing Up in Broken Home	0.43	-0.09	0.83	0.00	0.34	0.11	-0.01
	(0.17)	(0.03)	(0.21)	(0.04)	(0.23)	(0.03)	(0.03)
Age	-0.03	0.004	-0.04	-0.002	-0.01	-0.004	0.003
	(0.01)	(0.001)	(0.01)	(0.002)	(0.01)	(0.002)	(0.001)
Constant	1.07		-0.68		-2.35		
	(0.40)		(0.45)		(0.52)		

Notes: The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete).

Table 7. The Gender Gap in Schooling Achievement
SPS02

Variables	Repeating a Grade in Primary School		Repeating a Grade in Secondary School		Average Score during Secondary School [a]
	Coefficient	Marg. Effect	Coefficient	Marg. Effect	Coefficient
Male	**0.22**	**0.07**	**0.12**	**0.04**	**-0.31**
	(0.05)	**(0.01)**	**(0.05)**	**(0.02)**	**(0.04)**
Mother's Education [b]					
Secondary Education	-0.06	-0.02	0.02	0.01	0.05
	(0.06)	(0.02)	(0.06)	(0.02)	(0.04)
Some Tertiary Education	0.14	0.04	-0.06	-0.02	0.11
	(0.19)	(0.06)	(0.20)	(0.06)	(0.13)
Complete Tertiary Education	-0.29	-0.08	-0.13	-0.04	0.35
	(0.22)	(0.06)	(0.20)	(0.05)	(0.13)
Father's Education [b]					
Secondary Education	-0.17	-0.05	-0.05	-0.01	0.14
	(0.06)	(0.02)	(0.06)	(0.02)	(0.04)
Some Tertiary Education	-0.51	-0.13	-0.29	-0.08	0.23
	(0.16)	(0.03)	(0.16)	(0.04)	(0.10)
Complete Tertiary Education	-0.41	-0.11	-0.11	-0.03	0.21
	(0.16)	(0.04)	(0.15)	(0.04)	(0.10)
Background					
Growing Up in Poverty	0.25	0.08	-0.04	-0.01	-0.16
	(0.05)	(0.02)	(0.06)	(0.02)	(0.04)
Growing Up in Broken Home	-0.38	-0.13	0.04	0.01	0.10
	(0.11)	(0.04)	(0.13)	(0.04)	(0.09)
School Characteristics [c]					
Urban Primary School	-0.20	-0.07	-	-	0.02
	(0.08)	(0.03)	-	-	(0.08)
Urban Secondary School	-	-	0.40	0.10	0.22
	-	-	(0.24)	(0.05)	(0.16)
Private-Subsized Primary School	-0.10	-0.03	-	-	0.07
	(0.07)	(0.02)	-	-	(0.06)
Coorporation - Primary School	-0.45	-0.12	-	-	0.22
	(0.59)	(0.12)	-	-	(0.35)
Private Primary Schoo	-0.27	-0.08	-	-	0.09
	(0.12)	(0.03)	-	-	(0.09)
Private-Subsized Secondary School	-	-	-0.21	-0.06	0.13
	-	-	(0.06)	(0.02)	(0.05)
Coorporation - Secondary School	-	-	-0.42	-0.10	0.15
	-	-	(0.26)	(0.05)	(0.17)
Private Secondary School	-	-	-0.41	-0.10	0.24
	-	-	(0.12)	(0.03)	(0.10)
Constant	-0.18	-	-1.15	-	-0.33
	(0.13)	-	(0.27)	-	(0.17)

Notes: (a) The average score is standarized to have mean 0 and variance 1 in the population; (b) The baseline category is Primary Education; (c) In the case of the dummies controlling for the type of management the baseline category is Public School. Standard Errors are presented in parentheses.

Table 8A. Variables in the empirical implementation of the model
Outcome Equations

Variables	Hourly Wage [a]	Monthly Hours Worked [a]	Employment [a]	Accumulated Experience [b]	Educational Choice Model [c]
Gender Dummy	Yes	Yes	Yes	Yes	Yes
Region of Residence	Yes	Yes	Yes	-	-
Growing Up in Broken Home	-	-	-	-	Yes
Mother's Education	-	-	-	Yes	Yes
Father's Education	-	-	-	Yes	Yes
Growing Up in Poverty	-	-	-	Yes	Yes
Age	-	-	Yes	Yes	Yes
Type of Occupation	Yes	Yes	-	-	-
Type of Job	Yes	Yes	-	-	
Unobserved Ability	Yes	Yes	Yes	Yes	Yes

Notes: (a) Hourly wages, monthly hours worked and employment models are estimated for four different schooling categories (primary, secondary, some tertiary and complete tertiary) and three different levels of accumulated experience (less than 10 years, between 10 and 15 years, and more than 15 years). In each case, the labor market outcome refers to the previous month individual's outcome; (b) Accumulated experience is modeled with a multinomial choice model. The categories considered are: less than 10 years, between 10 and 15 years, and more than 15 years. The level of accumulated experience is the total work experience reported at the time of the interview;

Table 8B. Variables in the empirical implementation of the model
Auxiliary Measures

Variables	Average Grade in Secondary Education	Repeat Any Grade in Primary School	Repeat Any Grade in Secondary School
Primary School in a Urban Area (Dummy)	Yes	Yes	-
Secondary School in a Urban Area (Dummy)	Yes	-	Yes
Growing Up in Broken Home	Yes	Yes	Yes
Mother's Education	Yes	Yes	Yes
Father's Education	Yes	Yes	Yes
Growing Up in Poverty	Yes	Yes	Yes
Primary School System (Public, Private, etc.)	Yes	Yes	-
Secondary School System (Public, Private, etc.)	Yes	-	Yes
Unobserved Ability	Yes	Yes	1.0

Table 9. Model with Essential Heterogeneity
Gender Gap in Hourly Wages, by Schooling Level and Accumulated Experience [(a)]
SPS02

Variable	High School Dropouts			High School Graduates			Some Post-Secondary Education			College Graduates		
	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15 Years	More than 15 Years	Less than 10 Years	Between 10 and 15	More than 15 Years
Male	**-0.06**	**0.30**	**0.07**	**0.35**	**0.15**	**0.19**	**0.23**	**0.35**	**0.15**	**0.38**	**0.38**	**0.36**
	(0.29)	**(0.18)**	**(0.14)**	**(0.09)**	**(0.06)**	**(0.05)**	**(0.08)**	**(0.08)**	**(0.10)**	**(0.08)**	**(0.15)**	**(0.20)**
Employer or Self-Worker [(b)]	-0.41	-0.34	-0.30	0.19	-0.19	-0.23	0.22	0.06	-0.12	0.00	-0.10	0.41
	(0.37)	(0.15)	(0.10)	(0.11)	(0.08)	(0.06)	(0.12)	(0.14)	(0.14)	(0.15)	(0.20)	(0.39)
Domestic Service	-0.52	0.18	-0.27	-0.11	-0.13	0.16	-	0.08	-1.44	-0.11	-	-
	(0.37)	(0.24)	(0.20)	(0.16)	(0.17)	(0.17)	-	(0.28)	(0.61)	(0.50)	-	-
Professionals [(c)]	-	-	-	-1.04	-	-0.52	0.26	0.42	-0.11	-0.21	-0.18	-0.18
	-	-	-	(0.63)	-	(0.48)	(0.22)	(0.36)	(0.29)	(0.14)	(0.24)	(0.30)
Technicians and associate professionals	-	-	-	-0.96	-0.36	-0.40	0.03	0.26	-0.41	-0.11	-0.46	-0.03
	-	-	-	(0.28)	(0.20)	(0.15)	(0.18)	(0.25)	(0.23)	(0.18)	(0.30)	(0.35)
Clerks	-	-	-0.83	-1.22	-0.48	-0.43	-0.38	-0.11	-0.53	-0.55	-0.79	-0.56
	-	-	(0.60)	(0.25)	(0.18)	(0.13)	(0.19)	(0.26)	(0.24)	(0.19)	(0.39)	(0.47)
Service workers and shop and market sales workers	-	-0.57	-0.48	-1.66	-0.61	-0.84	-0.64	-0.46	-0.59	-	-0.84	-
	-	(0.48)	(0.32)	(0.25)	(0.18)	(0.13)	(0.20)	(0.26)	(0.24)	-	(0.52)	-
Skilled agricultural and fishery workers	0.39	-0.55	-0.78	-1.75	-0.83	-0.92	-0.44	0.47	-0.81	-	-	-
	(0.57)	(0.40)	(0.29)	(0.37)	(0.24)	(0.16)	(0.63)	(0.46)	(0.38)	-	-	-
Craft and related trades workers	0.25	-0.38	-0.57	-1.44	-0.68	-0.67	-0.57	-0.27	-0.63	-	-	-1.22
	(0.34)	(0.38)	(0.28)	(0.26)	(0.17)	(0.12)	(0.22)	(0.26)	(0.25)	-	-	(0.85)
Plant and machine operators and assemblers	0.69	-0.36	-0.57	-1.52	-0.72	-0.81	-0.80	-0.52	-1.11	-	0.59	-1.37
	(0.56)	(0.40)	(0.30)	(0.26)	(0.17)	(0.12)	(0.27)	(0.27)	(0.32)	-	(0.69)	(0.59)
Elementary occupations	0.35	-0.67	-0.63	-1.66	-0.80	-0.88	-0.91	-0.55	-1.18	-0.97	-1.75	-
	(0.32)	(0.38)	(0.28)	(0.26)	(0.20)	(0.13)	(0.28)	(0.30)	(0.28)	(0.38)	(0.50)	-
Central	0.48	-0.11	-0.13	-0.29	-0.21	-0.15	-0.05	-0.19	0.11	-0.13	0.38	-0.58
	(0.51)	(0.22)	(0.13)	(0.12)	(0.09)	(0.07)	(0.15)	(0.15)	(0.23)	(0.17)	(0.28)	(0.38)
South	0.41	-0.13	-0.03	-0.24	-0.07	0.03	-0.10	-0.13	0.11	0.03	0.42	-0.12
	(0.43)	(0.21)	(0.14)	(0.11)	(0.09)	(0.08)	(0.13)	(0.14)	(0.23)	(0.15)	(0.27)	(0.34)
Santiago	-0.25	0.36	0.19	0.22	0.25	0.27	0.08	0.20	0.12	0.35	-0.05	0.39
	(0.35)	(0.16)	(0.11)	(0.10)	(0.07)	(0.06)	(0.11)	(0.10)	(0.13)	(0.11)	(0.19)	(0.26)
Intercept	5.56	7.04	7.04	8.10	7.36	7.37	7.28	7.12	7.52	8.07	7.98	8.80
	(0.47)	(0.51)	(0.34)	(0.27)	(0.19)	(0.13)	(0.21)	(0.30)	(0.30)	(0.25)	(0.43)	(0.55)
Unobserved Heterogeneity	-0.20	0.71	-0.03	0.17	0.13	-0.19	-0.32	-0.30	-0.004	-0.39	-0.50	-0.89
	(0.13)	(0.43)	(0.07)	(0.15)	(0.11)	(0.09)	(0.15)	(0.17)	(0.20)	(0.22)	(0.39)	(0.51)

Notes: The accumulated experience corresponds to the retrospective information reported by the individual at the time of the interview. The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete). (b) For the characteristics of the type of job (employer or self-worker and domestic service), the baseline category is Public and Private Employees; (c) For the set of variables controlling for occupation characteristics (from Professionals to Elementary Occupations in this table) the baseline category is Legislators, senior officials and managers.

Table 10. Model with Essential Heterogeneity

Gender Gap in Hours Worked, by Schooling Level and Accumulated Experience [(a)]

SPS02

Variable	High School Dropouts			High School Graduates			Some Post-Secondary Education			College Graduates		
	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15 Years	More than 15 Years	Less than 10 Years	Between 10 and 15 Years	More than 15 Years	Less than 10 Years	Between 10 and 15	More than 15 Years
Male	**-0.06**	**0.18**	**0.14**	**0.08**	**0.10**	**0.07**	**0.17**	**0.12**	**0.10**	**0.02**	**0.00**	**0.08**
	(0.15)	**(0.13)**	**(0.08)**	**(0.07)**	**(0.03)**	**(0.03)**	**(0.05)**	**(0.04)**	**(0.05)**	**(0.06)**	**(0.08)**	**(0.10)**
Employer or Self-Worker [(b)]	-0.01	-0.12	-0.17	-0.53	-0.06	-0.16	-0.24	-0.31	-0.22	-0.09	-0.02	-0.07
	(0.18)	(0.11)	(0.06)	(0.09)	(0.04)	(0.03)	(0.08)	(0.07)	(0.07)	(0.11)	(0.10)	(0.20)
Domestic Service	0.18	-0.09	0.08	-0.25	0.00	-0.18	-	0.07	-0.75	-0.09	-	-
	(0.19)	(0.18)	(0.11)	(0.14)	(0.08)	(0.09)	-	(0.14)	(0.30)	(0.36)	-	-
Professionals [(c)]	-	-	-	-0.96	-	-0.08	-0.34	-0.45	-0.33	-0.20	-0.29	-0.15
	-	-	-	(0.55)	-	(0.26)	(0.15)	(0.18)	(0.15)	(0.10)	(0.13)	(0.15)
Technicians and associate professionals	-	-	-	-0.34	-0.05	-0.21	-0.42	-0.38	-0.22	-0.19	-0.19	-0.31
	-	-	-	(0.24)	(0.10)	(0.08)	(0.12)	(0.12)	(0.11)	(0.13)	(0.15)	(0.17)
Clerks	-	-	0.31	-0.21	-0.11	-0.25	-0.27	-0.34	-0.22	-0.02	-0.15	-0.02
	-	-	(0.34)	(0.22)	(0.09)	(0.07)	(0.13)	(0.13)	(0.12)	(0.14)	(0.19)	(0.24)
Service workers and shop and market sales workers	-	0.36	-0.27	-0.11	-0.11	-0.23	-0.38	-0.31	-0.28	-0.02	0.00	-
	-	(0.36)	(0.20)	(0.21)	(0.09)	(0.07)	(0.13)	(0.13)	(0.12)	(0.28)	(0.27)	-
Skilled agricultural and fishery workers	0.01	-0.10	-0.09	-0.31	-0.06	-0.22	0.11	-0.29	-0.09	-	-	-
	(0.29)	(0.29)	(0.19)	(0.30)	(0.12)	(0.09)	(0.41)	(0.23)	(0.18)	-	-	-
Craft and related trades workers	-0.11	0.07	-0.06	-0.23	-0.05	-0.23	-0.27	-0.33	-0.09	-	-	0.38
	(0.17)	(0.28)	(0.18)	(0.22)	(0.08)	(0.06)	(0.15)	(0.13)	(0.12)	-	-	(0.43)
Plant and machine operators and assemblers	0.06	0.03	-0.08	-0.09	-0.02	-0.16	-0.06	-0.25	-0.43	-	-0.06	0.02
	(0.28)	(0.30)	(0.20)	(0.23)	(0.09)	(0.06)	(0.18)	(0.13)	(0.16)	-	(0.36)	(0.29)
Elementary occupations	-0.16	0.01	-0.09	-0.28	-0.09	-0.27	-0.68	-0.64	-0.05	-	-0.52	-
	(0.16)	(0.28)	(0.18)	(0.22)	(0.10)	(0.07)	(0.18)	(0.15)	(0.14)	-	(0.26)	-
Central	0.05	-0.07	0.05	-0.04	-0.02	-0.02	0.13	-0.05	-0.12	-0.07	-0.26	-0.20
	(0.25)	(0.16)	(0.08)	(0.10)	(0.05)	(0.04)	(0.09)	(0.07)	(0.12)	(0.12)	(0.14)	(0.20)
South	-0.19	-0.01	-0.15	0.00	0.00	-0.04	0.07	-0.04	-0.07	-0.19	-0.22	-0.31
	(0.22)	(0.16)	(0.08)	(0.09)	(0.04)	(0.04)	(0.09)	(0.07)	(0.12)	(0.11)	(0.14)	(0.17)
Santiago	-0.09	-0.02	-0.02	0.07	0.05	0.01	-0.03	0.03	0.09	0.02	0.02	0.03
	(0.17)	(0.12)	(0.06)	(0.09)	(0.04)	(0.03)	(0.07)	(0.05)	(0.07)	(0.08)	(0.10)	(0.14)
Intercept	4.35	3.54	4.01	3.91	3.85	4.05	3.92	4.17	4.06	3.90	4.04	4.05
	(0.27)	(0.37)	(0.22)	(0.22)	(0.09)	(0.07)	(0.14)	(0.14)	(0.15)	(0.17)	(0.21)	(0.27)
Unobserved Heterogeneity	0.40	-0.39	0.23	-0.15	0.01	0.03	0.18	0.06	0.08	0.08	0.17	-0.04
	(0.13)	(0.26)	(0.06)	(0.12)	(0.05)	(0.05)	(0.10)	(0.08)	(0.10)	(0.13)	(0.17)	(0.22)

Notes: The accumulated experience corresponds to the retrospective information reported by the individual at the time of the interview. The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete). (b) For the characteristics of the type of job (employer or self-worker and domestic service), the baseline category is Public and Private Employees; (c) For the set of variables controlling for occupation characteristics (from Professionals to Elementary Occupations in this table) the baseline category is Legislators, senior officials and managers.

Table 11. Model with Essential Heterogeneity
Gender Gap in Employment Status, by Schooling Level and Accumulated Experience
SPS02

Variable	High School Dropouts [a]			High School Graduates			Some Post-Secondary Education			College Graduates [b]	
	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15	More than 15 Years	Less than 10 Years	Between 10 and 15 Years
Male	**1.40**	**0.35**	**-0.10**	**0.98**	**0.30**	**0.34**	**0.80**	**0.36**	**0.18**	**-0.12**	**-0.23**
	(0.54)	**(0.35)**	**(0.35)**	**(0.14)**	**(0.12)**	**(0.13)**	**(0.14)**	**(0.20)**	**(0.24)**	**(0.25)**	**(0.47)**
Central	-	-	-	-0.17	-0.09	0.00	0.03	0.42	0.42	-0.39	-
	-	-	-	(0.17)	(0.21)	(0.22)	(0.23)	(0.32)	(0.48)	(0.61)	-
South	-	-	-	0.16	0.05	-0.06	0.29	1.17	1.45	-0.36	-
	-	-	-	(0.17)	(0.20)	(0.22)	(0.23)	(0.37)	(0.62)	(0.59)	-
Santiago	-	-	-	0.17	0.27	0.10	-0.06	0.20	0.10	-0.19	-
	-	-	-	(0.14)	(0.16)	(0.16)	(0.18)	(0.26)	(0.33)	(0.33)	-
Number of Children	0.09	0.04	0.11	-0.11	-0.07	-0.07	-0.04	-0.03	0.01	0.14	0.17
	(0.10)	(0.13)	(0.10)	(0.05)	(0.05)	(0.05)	(0.07)	(0.09)	(0.10)	(0.13)	(0.21)
Intercept	-2.20	-0.26	0.13	-0.08	0.62	0.79	0.06	0.40	0.38	1.13	3.16
	(1.17)	(0.54)	(0.61)	(0.17)	(0.20)	(0.23)	(0.21)	(0.29)	(0.44)	(0.72)	(2.09)
Unobserved Heterogeneity	-1.65	-1.63	-1.64	0.37	0.21	0.10	0.07	0.07	0.22	0.59	-1.69
	(1.35)	(1.27)	(1.62)	(0.22)	(0.27)	(0.25)	(0.29)	(0.44)	(0.54)	(0.70)	(1.81)

Notes: The accumulated experience corresponds to the retrospective information reported by the individual at the time of the interview. The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete). (a) Among high school dropouts, the characteristics of the place of residence perfectly predict the labor status, so those variables are excluded in these cases. (b) For the group of individuals reporting more than 15 years of experience and a college degree, the gender dummy perfectly predicts the labor status: the 29 women in these category reported to be working (34 out of 37 males report to be working). Since the gender coefficient is the main interest of this table we do not include this model here.

Table 12. Model with Essential Heterogeneity
Gender Gap in Accumulated Experience, by Schooling Level
SPS02

Variables	High School Dropouts		High School Graduates		Some College		College Graduates	
	Between 10 and 15 Years	More than 15 Years	Between 10 and 15 Years	More than 15 Years	Between 10 and 15 Years	More than 15 Years	Between 10 and 15 Years	More than 15 Years
Male	**1.47**	**2.95**	**1.48**	**2.50**	**0.75**	**1.02**	**0.14**	**0.41**
	(0.23)	**(0.24)**	**(0.12)**	**(0.15)**	**(0.14)**	**(0.21)**	**(0.28)**	**(0.42)**
Mother's Years of Schooling	0.04	-0.02	0.03	0.03	-0.01	0.05	-0.04	-0.11
	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.04)	(0.06)	(0.09)
Father's Years of Schooling	-0.04	0.00	0.00	-0.02	-0.02	0.00	0.09	-0.06
	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.04)	(0.06)	(0.10)
Growing Up in Poverty	-0.21	-0.03	-0.16	-0.14	0.02	0.25	-0.30	0.79
	(0.24)	(0.22)	(0.12)	(0.14)	(0.19)	(0.26)	(0.42)	(0.69)
Age	-0.05	0.26	0.11	0.46	0.20	0.61	0.39	0.78
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.06)	(0.06)	(0.11)
Intercept	1.37	-10.45	-4.22	-17.06	-6.98	-22.97	-16.69	-25.84
	(1.29)	(1.21)	(0.64)	(0.97)	(1.00)	(2.73)	(3.54)	(4.42)
Unobserved Heterogeneity	1.19	-0.20	1.23	1.57	0.53	2.09	2.95	-1.71
	(0.74)	(0.17)	(0.28)	(0.36)	(0.45)	(0.96)	(1.55)	(3.10)

Notes: The accumulated experience corresponds to the retrospective information reported by the individual at the time of the interview. The table presents the results for three multinomial choice models (each for each schooling level). The baseline category is less than 10 years of accumulated experience.

Table 13. Model with Essential Heterogeneity
Gender Gap in Schooling Decisions
SPS02

Variable	Secondary School	Some Post-Secondary	College Graduates
Male	**-0.47**	**-0.55**	**-0.61**
	(0.11)	**(0.13)**	**(0.30)**
Mother's Years of Schooling	0.13	0.23	0.41
	(0.02)	(0.03)	(0.06)
Father's Years of Schooling	0.09	0.21	0.44
	(0.02)	(0.02)	(0.07)
Growing Up in Poverty	-0.03	-0.03	0.08
	(0.01)	(0.02)	(0.04)
Growing Up in Broken Home	0.53	1.02	0.46
	(0.22)	(0.30)	(0.71)
Age	-0.81	-1.25	-2.20
	(0.11)	(0.15)	(0.46)
Intercept	1.10	-1.66	-12.93
	(0.51)	(0.64)	(2.99)
Unobserved Heterogeneity	1.90	3.52	10.90
	(0.38)	(0.48)	(1.96)

Notes: The shooling level corresponds to the schooling level declared in the sample. Post-secondary education includes includes technical education (complete and incomplete). The baseline category is Primary School.

Table 14. Model with Essential Heterogeneity
Gender Gap in Hours Schooling Achievement
SPS02

Variables [a]	Repeating a Grade in Primary School	Repeating a Grade in Secondary School	Average Score during Secondary School [b]
Male	**0.26**	**0.17**	**-0.33**
	(0.05)	**(0.06)**	**(0.04)**
Mother: Secondary Education	-0.08	-0.04	0.10
	(0.07)	(0.07)	(0.04)
Mother: Some Tertiary Education	0.06	-0.20	0.23
	(0.21)	(0.22)	(0.12)
Mother: Complete Tertiary Education	-0.30	-0.18	0.38
	(0.25)	(0.23)	(0.12)
Father: Secondary Education	-0.20	-0.12	0.20
	(0.06)	(0.07)	(0.04)
Father: Some Tertiary Education	-0.61	-0.44	0.30
	(0.18)	(0.18)	(0.10)
Father: Complete Tertiary Education	-0.40	-0.17	0.24
	(0.17)	(0.17)	(0.09)
Growing Up in Poverty	0.28	0.04	-0.23
	(0.06)	(0.07)	(0.04)
Growing Up in Broken Home	-0.09	0.45	0.01
	(0.08)	(0.26)	(0.08)
Urban Primary School	-0.40	-	0.13
	(0.12)	-	(0.09)
Urban Secondary School	-	0.01	0.19
	-	(0.16)	(0.14)
Private-Subsized Primary School	0.00	-	-0.01
	(0.08)	-	(0.05)
Coorporation - Primary School	-0.57	-	0.26
	(0.68)	-	(0.32)
Private Primary Schoo	-0.11	-	-0.06
	(0.13)	-	(0.08)
Private-Subsized Secondary School	-	-0.20	0.12
	-	(0.07)	(0.05)
Coorporation - Secondary School	-	-0.47	0.16
	-	(0.28)	(0.15)
Private Secondary School	-	-0.28	0.17
	-	(0.14)	(0.09)
Intercept	-0.36	-1.17	-0.40
	(0.14)	(0.30)	(0.16)
Unobserved Heterogeneity	-0.98	-1.22	1.00
	(0.09)	(0.12)	-

Notes: (a) In the case of mother's and father's education the baseline category is Primary Education. In the case of the dummies controlling for the type of management the baseline category is Public School. (b) The average score is standarized to have mean 0 and variance 1 in the population. Standard Errors are presented in parentheses.

Table A1. Descriptive Statistics SPS02 by Gender

Variable (Dummy=1 if Apply)	Females		Males	
	Mean	Std. Dev.	Mean	Std. Dev.
Age	33.76	3.76	33.71	3.79
A. School Information				
Maximum Schooling Level = Primary Education	0.11	0.32	0.17	0.38
Maximum Schooling Level = Secondary Education	0.51	0.50	0.49	0.50
Maximum Schooling Level = Some Tertiary Education	0.26	0.44	0.24	0.43
Maximum Schooling Level = Complete Tertiary Education	0.11	0.31	0.10	0.30
A.1. Primary School				
Primary School in Urban Area	0.91	0.29	0.89	0.31
Repeating a Grade in Primary School	0.22	0.41	0.30	0.46
Was Primary School Public?	0.77	0.42	0.81	0.39
Was Primary School Private-Subsidized?	0.16	0.37	0.13	0.33
Was Primary School Managed by a Coorporation?	0.00	0.05	0.00	0.04
Was Primary School Private?	0.07	0.25	0.06	0.23
A.2. Secondary School				
Secondary School in Urban Area	0.98	0.14	0.99	0.12
Repeating a Grade in Secondary School	0.20	0.40	0.24	0.43
Was Secondary School Public?	0.70	0.46	0.70	0.46
Was Secondary School Private-Subsidized?	0.23	0.42	0.22	0.42
Was Secondary School Managed by a Coorporation?	0.01	0.08	0.02	0.13
Was Secondary School Private?	0.07	0.25	0.06	0.24
Average Grade in Secondary School	0.16	0.98	-0.17	1.00
B. Family Background				
Mother's Employment - Asalaried	0.56	0.50	0.55	0.50
Father's Employment - Asalaried	0.99	0.07	0.99	0.09
Total Number of Children	1.64	1.19	1.47	1.22
Mother's Education (years of schooling)	7.51	3.77	7.42	3.69
Father's Education (years of schooling)	8.14	4.11	7.91	4.00
Growing up under Poverty	0.28	0.45	0.35	0.48
Growing up in a Broken Home	0.96	0.20	0.96	0.20
C. Labor Market Variables				
Monthly Earnings	215,266	214,323	285,140	360,046
Hours Worked per Week	43.41	11.74	48.17	9.81
Hourly Wage	1,292	1,257	1,636	4,649
Working During Last Month	0.59	0.49	0.82	0.39
Total Work Experience since Jan. 1980	113.43	66.00	165.02	63.52
Less than 10 years of Experience	0.56	0.50	0.25	0.43
Between 10 and 15 years of Experience	0.26	0.44	0.34	0.47
More than 15 years of Experience	0.18	0.39	0.41	0.49
C.1 Type of Job				
Asalaried	0.81	0.39	0.80	0.40
Employer or Self-Worker	0.11	0.32	0.20	0.40
Domestic Service	0.08	0.27	0.00	0.02
C.2 Type of Occupation				
Administrative and Managerial Workers	0.03	0.17	0.06	0.24
Professionals	0.13	0.34	0.08	0.27
Technicians and associate professionals	0.14	0.35	0.11	0.32
Clerks	0.26	0.44	0.10	0.30
Service workers and shop and market sales workers	0.22	0.42	0.09	0.29
Skilled agricultural and fishery workers	0.01	0.09	0.06	0.23
Craft and related trades workers	0.04	0.19	0.23	0.42
Plant and machine operators and assemblers	0.04	0.19	0.17	0.37
Elementary occupations	0.13	0.34	0.10	0.31
D. Place of Residence				
North (I to III Regions)	0.13	0.33	0.11	0.32
Central (IV to VII Regions)	0.65	0.48	0.62	0.49
South (VIII to XII Regions)	0.23	0.42	0.26	0.44
Santiago (Region XIII)	0.43	0.49	0.42	0.49
Number of Observations		1,765		1,801

Note: The numbers presented in this table corresponds to the sample of individuals with ages between 28 and 40 years old at the time of the interview.