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The Two Faces of Knowledge Diffusion: the Chilean Case*

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ABSTRACT: This paper analyses the dynamics of return to knowledge where knowledge is acquired through the combination of interactive and individual learning. We suggest that in light of this new definition of knowledge, choosing the optimal level of education is no longer an individual exercise of present and future utility maximisation as suggested by more formal human capital theory (Becker, 1964). In fact, other external (environmental) variables might affect the individual decision of investment. We calculate the effect of individual and interactive learning in determining the wage of Chilean workers aged between 14 and 65.

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1. INTRODUCTION

Latin America is one of the most unequal regions in the world. Despite its fairly good economic performance, which has allowed a substantial reduction in poverty, inequality has almost never declined; showing, on the contrary, a substantial increase over the last two decades. The Chilean economy, in spite of its outstanding performance in the past decades, has not been immune to the increase in inequality widely registered throughout the region.

To give an idea of the magnitude of inequality we will quickly review some relevant statistics. Inequality in Chile is high both in absolute terms and in relative terms. In 1990, the Gini index calculated by Deininger and Squire (1996) placed Chile at the very bottom of a world list:

Table 1: Income Inequality, Selected Regions: 1990

	Percentage in national income divided by income quintiles				
Region	Gini	1	2	3 & 4	5
Sub-Saharan Africa	46.95	5.15	8.94	33.54	52.37
Latin America and the Caribbean	49.31	4.52	8.7	33.84	52.94
East Asia and the Pacific	38.09	6.84	11.3	37.53	44.33
South Asia	31.88	8.76	12.91	38.42	39.91
Eastern Europe	28.94	8.83	13.36	40.01	37.8
Middle East and North Africa	38.03	6.9	10.91	36.84	45.35
Developed countries	33.75	6.26	12.15	41.8	39.79
Chile	56.49	3.52	6.62	28.91	60.95

Source: Deininger and Squire, 1996.

A similar picture emerges if we look at the standard of living. "The persistence of high levels of unemployment for long periods of time and the severe drop and slow recovery of the real wages led [in the last three decades] to a deterioration in worker's standards of living" (Raczynski and Romaguera, 1995: 286). This can be deduced from several indicators. An effective way to monitor changes in living standards is by looking at changes in the per capita consumption. The two financial crises (1975 and 1982) had of course severe impacts on consumption. Moreover, the 1982 crisis was followed by a long recession, which lasted four years. The recovery phase, which started in 1986, was slow, and in 1989 the index still remained 4 points below the 1981 level. Alongside the decline in consumption, the economy witnessed a further deterioration in the distribution of expenditures across income groups.

Table 2: Household Expenditure, Greater Santiago

Quintiles	1969	1978	1988
1 (lowest)	7.6%	5.2%	4.4%
2	11.8%	9.3%	8.2%
3	15.6%	13.6%	12.7%
4	20.6%	21.0%	20.1%
5 (highest)	44.5%	51.0%	54.6%

Source: Raczynski and Romaguera, 1995.

The table above shows a clear increase in expenditure concentration: the richest quintile of the Greater Santiago population gained more than 10% of overall expenditure in less than twenty years. Ricardo Ffrench-Davis observed in 1983 that over the first nine years of military regime "with households divided into five quintiles, […] the poorest reduced their consumption by 31 percent between the two observations, while the second and third quintiles cut back by 20 percent and 12 percent respectively. On the other hand, the highest income quintiles concentrated the counterpart of the deteriorated position of the other groups" (Ffrench-Davis, 1983: 23). The high level of inequality in Chile is largely due to inequality in wages. The average Gini index calculated for household income coming exclusively from labour is 0.51, while the index calculated using all sources of household income is only one percentage point higher. This data suggests that the direct source of inter-household inequality is income from work, rather than capital income, as is often believed (Beyer, 2000).

One of the plausible causes of such inequality might arise in the asymmetrical distribution of knowledge, coupled with the kinds of increasing returns to education observable in the Chilean labour market. In this paper we study the dynamics of returns to knowledge, where knowledge is acquired through a combination of interactive and individual learning. We suggest that in the light of this new definition of knowledge, choosing the optimal level of education is no longer an individual exercise of present and future utility maximisation as suggested by more formal human capital theory (Becker, 1964). In fact, other external (environmental) variables could affect the individual decision on investment. We develop a model which allows us to calculate the returns from both individual learning (i.e. schooling) and interactive learning (i.e. face-to-face interaction and the adoption of information and communication technology). We then apply this model to the Chilean labour market.

The work is structured as follows: the next section reviews briefly the literature on returns to schooling in Chile, then we present a critique of this literature and develop a model which takes into consideration the twofold definition of learning mentioned above. The fourth section presents the description of the data used as well as the model's results. Finally, section five concludes the work, presenting the policy implications of the core results and some suggestions for further developments.

2. RETURNS TO SCHOOLING: THE CASE OF CHILE

Two main propositions have been put forward to explain the increase in wage dispersion: first, that the increase in the gap between skilled and unskilled workers has been caused by trade liberalisation, and secondly, that technological changes, biased against less skilled workers, have actually generated the increase in inequality. The technological argument appears to be empirically stronger. In fact, a vast number of studies show, in one way or another, that technological changes have penalised less skilled workers in terms of both labour demand and wage differentials.

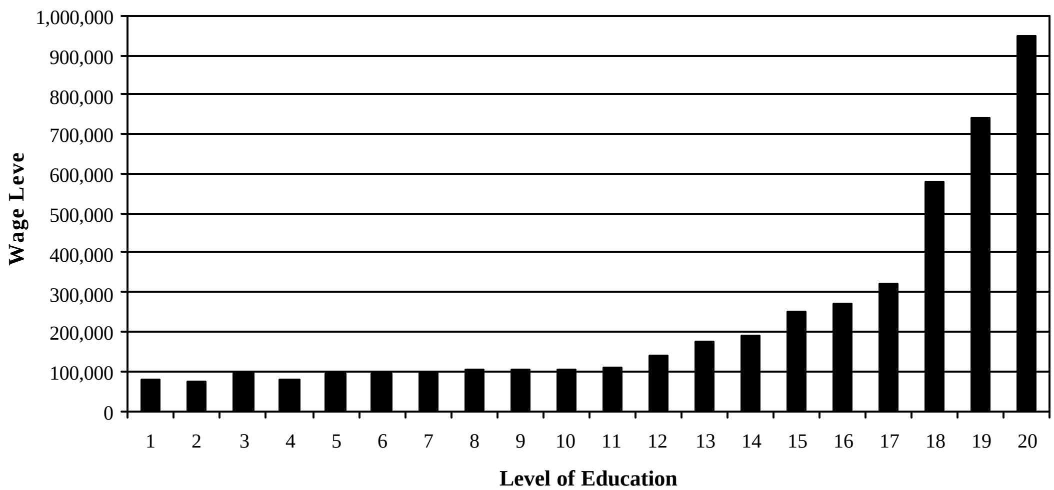
Several studies have focused their attention on the impact of schooling on wage dynamics, using the years of schooling as a proxy for skills. Bravo and Marinovic (1997) studying Chilean household survey data[1] observe "that relative wages have moved progressively in favour of more educated workers since 1975. This fact is reflected in wider gaps between workers with more versus less schooling, especially among the entrants of the labour market" (Bravo and Marinovic, 1997: 25). Moreover, they note that "there were important changes in the distribution of employment by schooling and occupational categories within economic sectors. All of them reduced the share of less educated workers and almost all diminished the percentage of blue-collar workers. On the other hand, the employment of workers with more schooling and higher positions increased in all economic sectors" (Bravo and Marinovic, 1997: 37)

Interesting results found by Beyer (2000) shed some light on the linkage between high education and inequality. He observed that, in most recent years, the impact of schooling is hardly noticeable among individuals with 12 or less years of schooling: the income curve for this group is practically flat. The figure presented below, based

[1] The data used in this work are the CASEN household survey and the *Encuesta de Ocupación y Desocupación* of the University of Chile.

on the 1994 edition of the *Enquesta* CASEN, shows the wage relationship with respect to educational levels.

Figure 1. Wage of Full-time Male Workers: 1994
(Resident in Urban Areas and aged between 25 and 54)

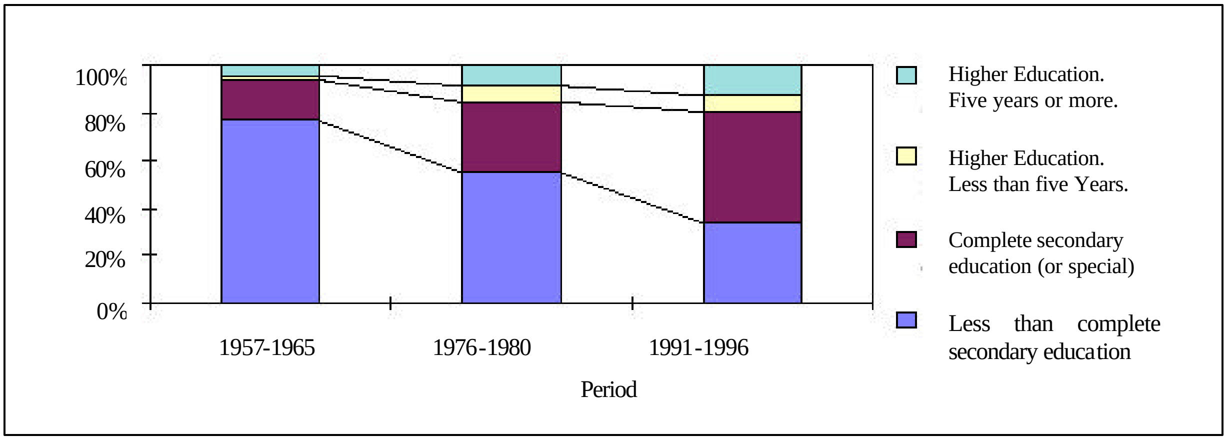


Source: Beyer, 2000.

The ideal curve binding the twenty observations of the graph grows in an exponential fashion. This suggests, as a first approximation, that the returns from education are not constant for different levels of schooling. In other words, an additional year of schooling begins to have a significant impact on a person's income only at high educational levels. Beyer (2000) corroborates this result in estimating a wage equation for different years and for different levels of education. The results of this exercise are extremely interesting: in 1996 additional years of schooling in elementary education had a marginal effect on the wage of less than 4%; the corresponding return to secondary education is approximately 10%. In higher education, however, it soars to more than 20%. The author argues that this relative structure has not always been present in the country: in 1960, marginal private returns to elementary and secondary education were around 10% and 20% respectively, while the return to university education was 13%. In 1970 the return to elementary and secondary education held steady, whereas returns to higher education reached 20%. During the 1980s, the gap in returns to education increased sharply, and in 1990 the distance between the returns to secondary and university education was approximately 12 percentage points. These results are particularly different from those usually obtained for developed countries, where the returns to education usually have a constant if not a decreasing relative structure.

Similar results to those obtained by Beyer (2000) had been attained by Bravo and Marinovic (1997) in a previous work. The authors studied the returns to education in the Great Santiago area using the *Encuesta de Ocupación y Desocupación* of the University of Chile. First, they showed that the level of schooling increased substantially over time, as shown in Figure 2 below.

Figure 2. Distribution of Years of Schooling among Full-time Workers



Source: Bravo and Marinovic, 1997

In 1957 more than 80% of the full-time employees had less than 12 years of education, while forty years later this percentage had dropped to 32%. The number of people with university education has also increased substantially over the same period. When looking at the returns to education, the authors conclude that the difference in the returns to schooling between workers with incomplete primary education, complete primary education, and incomplete secondary education has disappeared over time. The wage-education curve, substantially flattened in its first part, jumps to much higher values once it exceeds the twelfth year of education[2].

An interesting study conducted by Bravo, Contreras and Medrano (1999) points out that the return to computer use in Chile is extremely high in comparison to those earlier observed by Krueger (1993) for the USA. Using the *Encuesta de Ocupación y Desocupación* of the University of Chile and the *International Adult Literacy Survey*

(IALS) for the year 1998, the authors estimate a wage equation to calculate the magnitude of the returns to computer use. Not to incur any omitted variable problems, the authors use a comprehensive list of control variables (wider than those used by Krueger) which includes: education, potential and effective experience, economic sectors, level of education of the father, quality of education, a set of proxies to account for ability (e.g. number of repeated school years), and biomass (calculated as [kg/(m^2)]). The inclusion of a wide set of control variables allows the authors to overcome some of the major criticisms made of previous works. DiNardo and Pischke (1996) have asserted that those workers that use computers are also the most qualified workers, and therefore would earn higher salaries even if they were not using computers. Bravo, Contreras and Medrano argue that controlling for the level of education of the father and ability allows them to overcome this problem. The results obtained undoubtedly suggest that returns to computer use are extremely high, ranking between 28% and 32%. These figures are approximately one third higher than those estimated for developed countries. This difference can be explained by the larger number of people who have access to computers in developed countries compared to Chile. A final conclusion drawn by the authors is that technological changes tend to have a stronger impact on the wage structure of developing economies than on that of developed countries.

The picture that comes out from these studies is that of a country dominated by self-reinforcing mechanisms which tend to widen the gap between those who have high levels of education and access to modern technologies, and those who have not. Unfortunately, the nexus between increasing returns to education and the adoption of new technologies is not investigated deeply enough. In our understanding, technological changes advantage those who are able to gain from them, who are usually in the most skilled and wealthy layers of the society. In other words, technology can trigger a *poverty trap*, marginalising those unable to use it, and widening the gap between skilled and unskilled workers (this would explain the sharp increase in returns to schooling after the twelfth year of education).

In the next section we will argue in favour of the existence of a *poverty trap* through the development of a model which disentangles the action of learning into individual learning and interactive learning. The main idea is that those people who

[2] It is important to mention that in the Chilean school system, more than 12 years of education means completed secondary school education.

have high levels of schooling and high access to ICT will be able to gain the most from interactive learning.

3. Individual Learning and Interactive Learning: Modelling Dynamic Inequality

In this section we depart from the assumption that the learning process of each individual can be divided into two different processes: an individual learning process (in which each individual decides how much to invest in formal education such as schooling), and an interactive learning process (through which individuals exchange information in a more informal – face to face – manner). This idea is in the line of thought of the 'peer effects' and 'network externality' literature. Classic studies of the learning process suggest that this amounts to much more than formal schooling and indicates the key importance of associating with peer groups, for example in actual working environments (e.g. Arrow, 1962; Rosenberg, 1982; Bénabou, 1993, 1996a,b). Recently, several empirical studies tried to measure the impact of local spillovers such as network externalities and learning from others. Authors like Case and Katz (1991), Brock and Durlauf (1995), Glaeser, Sacerdote and Scheinkman (1996), Goolsbee and Klenow (1999), and Hoxby (2000) have proved in various ways the importance of networks externalities in determining individual behaviours.

In our model we define the two processes of learning as linked by a relation similar to the one that links firms' spending on R&D and their ability to gain from technological spillovers. In 1989 Cohen and Levinthal studied the effect of investment in R&D at the firm level and suggested that "R&D not only generates new information, but also enhances the firm's ability to assimilate and exploit existing information… [W]hile R&D obviously generates innovations, it also develops the firm's ability to identify, assimilate and exploit knowledge from the environment – what we call a firm's 'learning' or 'absorptive' capacity" (Cohen and Levinthal, 1989: 569). This twofold effect is what they called the 'two faces of R&D'.

This idea could be translated, *mutatis mutandis*, into the individual decision to invest in education: an individual's capacity to absorb externally generated knowledge depends on its investment in individual learning. In other words, we could say that investments in individual learning have a double (face) effect: directly augmenting the educational level, and indirectly augmenting the capacity for learning through direct interaction.

Along the lines of the model proposed by Cohen and Levinthal, we can formally define a single equation to describe the level of *knowledge* (human capital) of each agent:

$$K_i = E_i + I_i\left(y_i,\ q_n,\ \frac{\sum_{j\in n} E_j}{N-1}\right) \tag{1}$$

where E_i is the level of education obtained by individual i through a formal process of individual learning, and I_i is the level of education of individual i obtained through the process of informal interactive learning. The latter process of learning is function of three variables: agent i's absorptive capacity (y_i); the degree of connectivity of the network (n) within which agents interact (q_n); and the average level of education of other agents $\left(\frac{\sum_{j\in n} E_j}{N-1}\right)$. It is important to note that in this model the absorptive capacity is a function of E_i with positive first derivative and negative second derivative (i.e. individual learning increases absorptive capacity at a decreasing rate). This formalisation resembles the basic structure of peer effects models (the *baseline model*), which have been commonly used to study the distributional problems such as disparity in education opportunity or income inequality[3]. Indeed, the difference of this formalisation is its non-linearity in peers' mean achievement.

Back in 1966 Nelson and Phelps suggested that returns to schooling are higher in a dynamic environment because education improves the workers' access to information and their ability to decode and understand new information. We will push this idea further in saying that achieving high levels of education through individual learning will facilitate the second[4] phase of the learning process (interactive learning). This fact is captured in the knowledge equation above by the parameter y_i – absorptive capacity. Furthermore, following the line of reasoning of Nelson and Phelps, we assume that interactive learning will be more productive the more advanced and connected is the surrounding environment. These two elements are

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[3] The baseline model can be express as $y_{ij}=a+b\bar{y}_{j,-i}+X_{ij}c$ where y_{ij} is some outcome for person i in group j, $\bar{y}_{j,-i}$ is the mean value of the outcome for all the people in group j except for person i, and X_{ij} is a vector of other factors that affect person i's outcome (Hoxby, 2000; Durlauf, 1996).

[4] We call interactive learning the 'second phase of the learning process' without necessarily implying a rigid temporal relation between the two aspects of the learning process.

captured in the knowledge equation by q_n and $\frac{\sum_{j \in n} E_j}{N-1}$, respectively the degree of connectivity of the agent (within a particular network) and the average level of education of other agents. By investing in individual learning, each person will become more educated but will also *learn how to learn*, becoming more able to exploit the opportunities provided by the surrounding environment. In the words of Cohen and Levinthal, each individual will augment her/his absorptive capacity. This implies that investment in knowledge will display increasing returns. The presence of increasing returns might then generate a situation similar to that described above as a *poverty trap*: those people who have initially invested little in individual learning (i.e. with an initially low level of education) will probably be unable to exploit the increasing returns, being trapped in a lower equilibrium. On the other hand, if a person could initially invest in individual learning and break out of the trap, she/he will continue to learn indefinitely. From this theoretical framework we can draw two main inferences, which will be the core hypotheses of our model. First, the impact of individual learning on returns to wages is, in fact, overestimated if considered separately from the impact of interactive learning; second, the impact of interactive learning is stronger the higher is the level of individual learning.

3.1 THE MODEL SPECIFICATION

An empirical test of this hypothesis can be developed using a structure similar to the one proposed by Mincer. The so-called Mincerian earnings function defines the logarithm of the current income as a function of years of schooling, work experience and individual ability:

$$\ln W = \alpha + rs + \ln g(t-s) + \varepsilon \qquad (2)$$

Following the idea described above according to which knowledge accumulated by each individual is the combination of two separate (but certainly interrelated) processes of learning (i.e. individual and interactive learning) we can rewrite equation (2) as follows:

$$\ln W = a + bK + e \qquad (3)$$

For simplicity we have omitted the experience term, having now replaced the years of schooling with a more comprehensive index of knowledge. Combining equations (1) and (3) we derive the following function:

$$\ln W_i = a + b\left[E_i + I_i\left(y_i,\ q_n,\ \frac{\sum_{j \in n} E_j}{N-1}\right)\right] + e \tag{4}$$

Having described the relation between y_i, q_n, and $\frac{\sum_{j \in n} E_j}{N-1}$ as characterised by self-reinforcing effects (i.e. the higher agent's i absorptive capacity is, the more she/he will gain from being well connected in a highly knowledgeable environment), we expect a non-linear relation between these variables:

$$\ln W_i = a + b\left(E_i + y_i\, q_n\, \frac{\sum_{j \in n} E_j}{N-1}\right) + e \tag{5}$$

Earlier we have defined absorptive capacity (y_i) as a positive function of the individual education level (E_i), therefore approximating y_i with E_i will not lead us to any major loss of information:

$$\ln W_i = a + b\left[E_i + E_i q_n\, \frac{\sum_{j \in n} E_j}{N-1}\right] + e \tag{6}$$

The subscript index i refers to the individual while the subscript n refers to the neighbourhood in which the individual lives. This geographical indexation will allow us to pick up neighbourhood level differences and to define the variables $\frac{\sum_{j \in n} E_j}{N-1}$ and q_n in the empirical estimation. Equation (6) can be rewritten as:

$$\ln W_i = a + bq_n m_n + bE_i + e \tag{7}$$

where $E_i \frac{\sum_{j \in n} E_j}{N-1}$ is set equal to m_i. Now we define the degree of connectivity as:

$$q_n = j + \Omega D_n \tag{8}$$

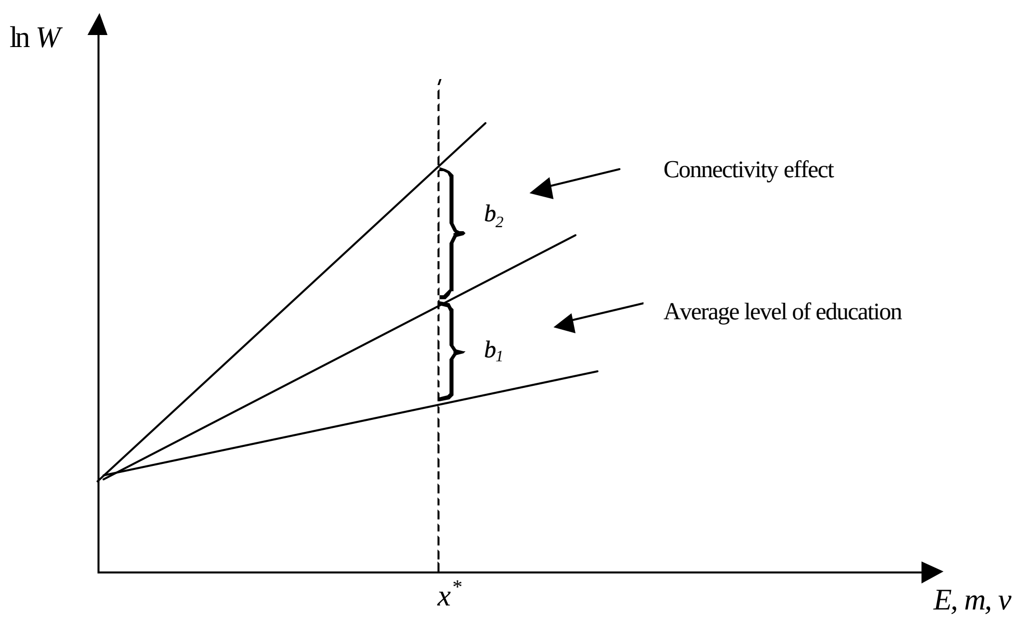
where D_n is a dummy variable characterising the index of connectivity (e.g. households which have access to computers or telephone lines).

We can now rewrite the wage equation as:

$$\ln W_i = a + bE_i + b_1 m_n + b_2 v_n + e \tag{9}$$

where v_n is equal to $D_n m_n$, b_1 is equal to $b\ j$, and b_2 is equal to bW. Equation (9) is a linear regression which decomposes the return to knowledge into three major effects: individual learning, environmental conditions (i.e. average level of knowledge of the surrounding environment of each agent), and degree of connectivity. We will argue that estimating this equation will give us a better measure of the return to knowledge than those obtained estimating a classic Mincerian equation. The additional information is brought into the picture by the introduction of a more comprehensive definition of knowledge, able to combine the two faces of the learning process. In fact, we will argue that estimating a traditional Mincerian equation without including the interactive learning term generates upward biased results.

More should be said about the interpretation of the three b coefficients. The first b is the return to formal education and it has a very similar interpretation to those conventionally given to returns to schooling. b_1 should be interpreted as the contribution to returns to knowledge given by the surrounding environment in which each person lives and interacts. Finally, b_2 represents the return to connectivity: access to ICT (e.g. access to telephone line, internet and email) will generate higher returns to education. The figure below shows how each component of the wage equation might affect the actual wage.



The different slopes of the three different curves plotted in the figure above reflect the fact that individual learning is interacting with the other two variables. This also reflects our expectation to observe increasing effects of b_1 and b_2 for higher levels of formal education.

With respect to the definition of neighbourhood it is important to mention here that each person is at the same time a member of several neighbourhoods, some of which are purely geographical, while others are *social neighbourhoods*. In other words, we can define a neighbourhood as the group of people who live in the same street, but we can also define a neighbourhood as the group of people who work in the same place, are acquainted with the same people, and share the same kind of interests. Indeed, most people would argue that the most fruitful interactions do not take place within our geographical neighbourhood but within some kind of *social neighbourhood*[5]. Therefore, it is important to consider all the possible dimensions of a neighbourhood in our analysis.

4. THE MODEL ESTIMATION

In this section we will present the main results obtained from the estimation of the model developed above. More precisely, we have estimated several wage equations, all of which are derived from equation (9). We will first describe the data used for this purpose, then we will show the main results of the empirical estimations, confronting them with the previous results in the literature.

4.1 DATA DESCRIPTION

The data used in this paper are obtained from three independent sources: the *Caracterización Socioeconómica Nacional* (CASEN) jointly conducted by the Department of Economics of the University of Chile and the Chilean Ministry of Planning (MIDEPLAN), the *Encuesta de Ocupación y Desocupación* of the University of Chile, and finally, the International Adult Literacy Survey (IALS) also conducted by the University of Chile.

The first CASEN survey was conducted in 1985, and other surveys followed in 1987, 1990, 1992, 1994, 1996, and 1998 (the CASEN 2000 is not yet available). These

[5] I am grateful to Osvaldo Larañaga, Dante Contreras and all the participants in the seminar held in the Economics Department of the University of Chile during my visit to the department, for pointing out this important differentiation between geographical and social neighbourhoods.

surveys, which cover the whole country, are considered the best available source of information on households. They provide information on demographic features; characteristics of the dwelling; access to utilities and public services; educational attainments; health conditions; health insurances; health services used and benefits received; occupation and employment; and income.

The *Encuesta de Ocupación y Desocupación* has been carried out every year since 1957. It covers a sample of approximately 4000 households located in the Great Santiago area[6]. The data collected cover demography; occupations, education and wages. The 1998 survey includes additional information on effective years of working experience; number of repeated school years; kind of school attended (characterised according to the funding system[7] and the rural/urban location); parents' level of education; religion; weight; height; and finally, use (or not) of a computer at work.

The *International Adult Literacy Survey* is probably the most complete survey in terms of information on the level and quality of education of the Chilean population. This survey has been conducted in thirteen countries[8], with Chile the only Latin American country appearing in this group. Moreover, alongside Poland, it is the only LDC included in the group. The survey, carried out in Chile in 1998, collected an extremely large amount of information for a sample which covered 3500 households homogeneously distributed around the country. Data are collected for all people aged between 15 and 65. The kind of information collected aims, among other targets, to define clearly and unambiguously the level of education and ability of workers across the country.

These three surveys are complementary rather than substitutes. Each one contains some information that is not included in the others. Therefore using the three databases and comparing the results will enrich our analysis as well as confirm its robustness and consistency. The variables of interest were the logarithm of wages, years of schooling, access to telephone lines, and use of computers at work. It is important to mention that data on access to telephones were only available in the CASEN survey, while data on the use of computers were available in the *Encuesta de Ocupación y Desocupación* and the *International Adult Literacy Survey.*

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[6] This region, called Región Metropolitana, covers 42% of the economically active national population (see: Bravo et al. 1999:7).

[7] Chilean schools can be entirely funded by the government, partially funded by the government or entirely private.

The geographical neighbourhoods have been defined at two levels of aggregation: *comuna* and *segmento*. The former, available only in the CASEN survey, identifies 243 districts, which cover the whole country. The latter, available in the CASEN survey and in the *Encuesta de Ocupación y Desocupación*, identifies a much smaller geographic entity, which can be associated with a block of buildings not interrupted by a street. In the CASEN survey there are 8283 *segmento* (this number drops to 7951 when we consider only workers and employees aged between 14 and 65), while for the Great Santiago area there are 292 *segmento*. Using the geographic neighbourhoods we defined the neighbourhood's average coverage of telephone lines, the neighbourhood's average number of computer users, and the neighbourhood's average level of education.

The *social neighbourhoods* were defined in two ways: as the 'work environment neighbourhoods' and as the 'social-affinity neighbourhoods'. The first category of *social neighbourhoods* was defined using information on the sector and on the city in which each person works (this information was available in the CASEN survey and in the *Encuesta de Ocupación y Desocupación*). We grouped together all people who work in the same sector[9] and who live in the same city. In the case of the *Encuesta de Ocupación y Desocupación*, which covers only the metropolitan area, we considered only the economic sectors in order to create work environment neighbourhoods. In this way we obtained 1764 neighbourhoods for the CASEN survey, and 705 for the *Encuesta de Ocupación y Desocupación*. The 'social-affinity neighbourhoods' have been defined only for the IALS database using special information on the quantity and quality of reading and on the kind of social interests[10]. We have constructed social-affinity neighbourhoods using principal component and cluster analysis. Through the methodology of principal components we identified the most significant variables for our analysis. Using a large set of potential variables, we selected those which explain a relatively large amount of the variability of the whole information set. Subsequently, we used a non-hierarchical clustering methodology to define group agents into k clusters. More precisely, we used the *k-means* clustering approach. This technique first defines k random clusters, and then moves objects (people in our case)

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[8] Belgium, Canada, Germany, Ireland, New Zealand, Northern Ireland, Poland, Sweden, Switzerland (French and German cantons), The Netherlands, United Kingdom, and United States.

[9] The level of aggregation identifies nine macro sectors (agriculture, mining, manufacturing, electrical, construction, trade, transport, financial sector, services).

between those clusters, with the goal of minimising variability within clusters and maximising variability between clusters. Since we have used more than one variable to define the clusters, the distances (variability) within and between clusters were measured in multi-dimensional space using Euclidean distances. In this way we generate 100 clusters, which are significantly heterogeneous among themselves, but each cluster is a homogeneous environment[11].

Below we report a statistical summary of the main variables used in the empirical analysis. We present three tables, each one referring to a different database.

Table 3. Description of Variables: Survey CASEN 1998
(Full time Employed Workers aged between 14 and 65)

Variable	Obs	Mean	Std. Dev.
Schooling	39329	9.915762	4.092142
Log of Wage	39418	11.74482	0.672038
Scho. by com.	39619	9.916283	1.586402
Scho. by seg.	39610	9.914581	2.870197
Scho. by w_n	39617	9.914343	2.829238
Telephones	31899	0.366030	0.481725
Tel. by com.	39619	36.59558	21.67438
Tel. by seg.	38835	36.12846	37.37153
Tel. by w_n	39541	36.83094	28.00059
m comuna	39329	100.8417	50.39584
v comuna	39329	4293.344	4264.573
m segmento	39329	106.5556	66.38665
v segmento	38549	5070.602	7045.457
m w_n	39329	106.3365	68.61727
v w_n	39251	5199.579	6529.566
segmento	39619	4006.577	2308.178
comuna	39619	8603.16	3808.521
work_n	39619	1336.338	555.4374

[10] A detailed list of the variables used to construct 'social-affinity neighbourhoods' is available from the author.
[11] For an extended discussion of principal component and cluster analysis see van Ooyen (2001).

Table 4. Description of Variables: Survey '*Encuesta de Ocupación y Desocupación*' 1998
(Full time Employed Workers aged between 14 and 65)

Variable	**Obs**	**Mean**	**Std. Dev.**
Schooling	2570	11.91323	3.689361
Log of Wage	2556	12.20511	0.748600
Scho. By seg.	2570	11.91323	2.516178
Scho. By w_n	2570	11.91323	2.770627
Computer	2180	0.3811932	0.4857912
Comp. By seg.	2521	40.8049	29.73077
comp. By w_n	2568	41.06695	33.58094
m segmento	2570	148.2537	69.91123
v segmento	2521	7342.507	7962.326
m w_n	2570	149.5984	75.37474
v w_n	2568	8087.169	8374.829
Segmento	2570	145.679	85.04472
Work_n	2570	36.27432	26.15741

Table 5. Description of Variables: *International Adult Literacy Survey*, 1998
(Full time Workers aged between 15 and 65)

Variable	**Obs**	**Mean**	**Std. Dev.**
Schooling	1536	9.66276	4.430521
Log of Wage	1352	14.0357	.9349546
Scho. By s_n.	1536	9.66276	3.173708
Computer	1536	0.222005	0.41573
Comp. by s_n.	1536	22.20052	20.19605
mw	1536	103.4348	66.6126
vw	1536	3344.395	4119.096
Social_net	1536	48.57357	29.15614

We define the two variables v_n and m_n, described in section three, using both levels of geographical aggregation and all the definitions of social neighbourhoods identified above.

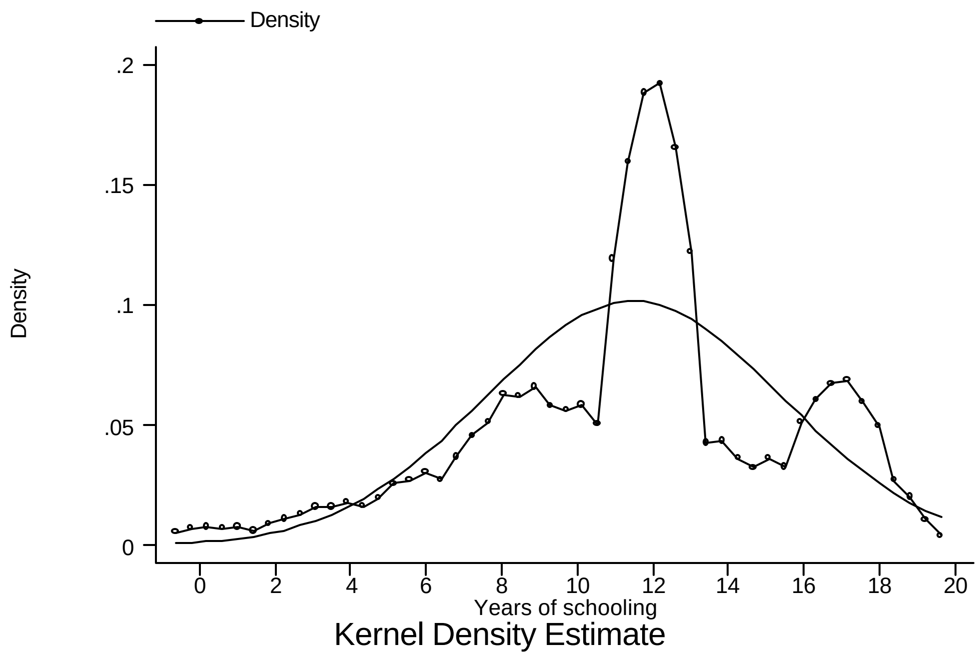
In the graph below we plotted the kernel density function of schooling to study how years of schooling are distributed among the working population[12]. It is interesting to observe (apart from the absolute maximum in correspondence to 12 years of schooling) the presence of a local maximum at the right of the mode of the

[12] The following analysis is solely based on the *Encuesta de Ocupación y Desocupación*, as the three surveys do not present particularly interesting differences.

distribution. This implies that there is a considerably large group of people endowed with relatively high levels of education (i.e. more than 12 years of schooling), which will give them a substantial comparative advantage.

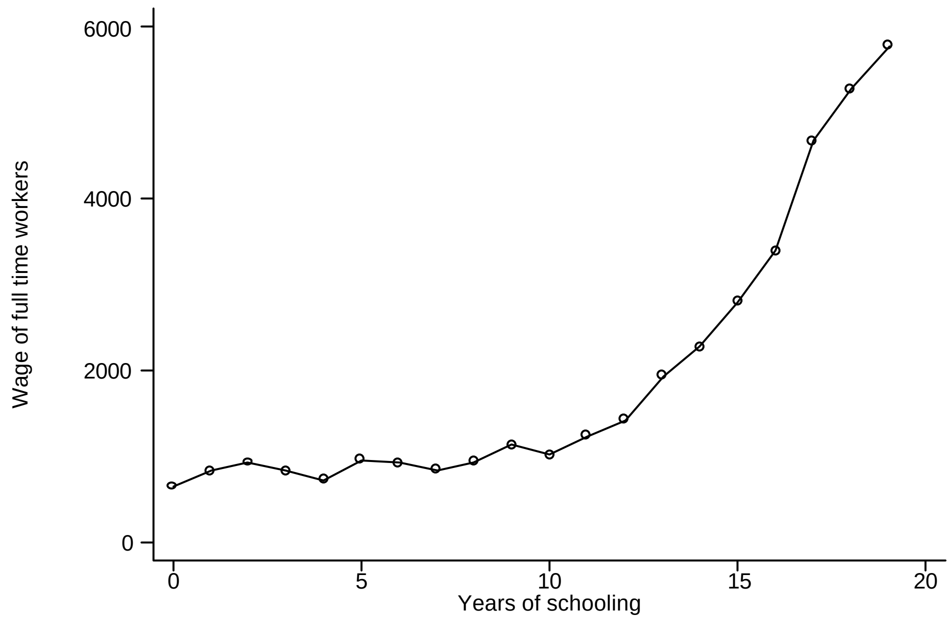
Figure 3. Density function of Years of Schooling

(Full time Employees aged between 14 and 65)



If we plot the average level of education against the average level of wages we can clearly see how the comparative advantage mentioned above will allow the group of most educated workers to be on the steep part of the wage curve.

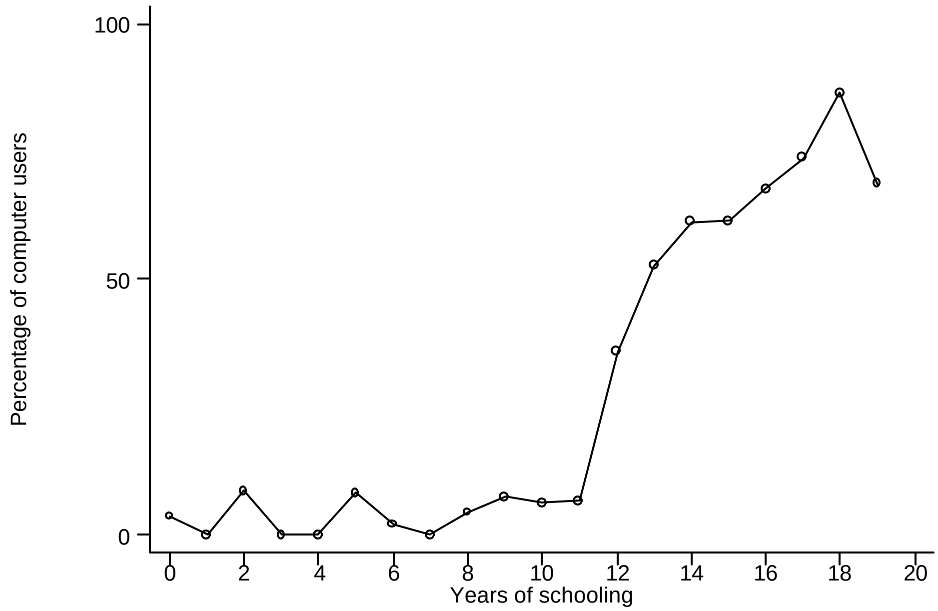
Figure 4. Wage against Years of Schooling
(Full time Employees aged between 14 and 65)



Next, we observe the distribution of computer users by levels of education: it is extremely important to note how the number of computer users increases sharply exactly in correspondence with the sharp increase of returns to education (i.e. 12 years of schooling). The shape of these curves unmistakably suggests the existence of a strong relation between wages, use of computers and level of education. What is left unexplained is the causal direction of this relation. A plausible conjecture is that high levels of education imply higher possibility of using computers at work as well as higher ability in using new technologies. Consequently, skilled workers will earn considerably more than unskilled workers. Indeed, we envisage a (vicious) cumulative effect, which works in the direction of widening the skilled/unskilled wage gap.

Figure 5. Percentage of computer users by levels of education

(Full time Employees aged between 14 and 65)



This phenomenon of cumulative advantages (i.e. higher level of education, higher probability of using new information and communication technologies, higher probability of being in the upper part of the wage distribution) becomes even more evident if we consider as the unit of investigation, the geographical neighbourhood rather than the individual[13]. In fact, the correlation between level of education and number of computer users is about 0.80[14], suggesting the presence of very homogeneous geographical neighbourhoods.

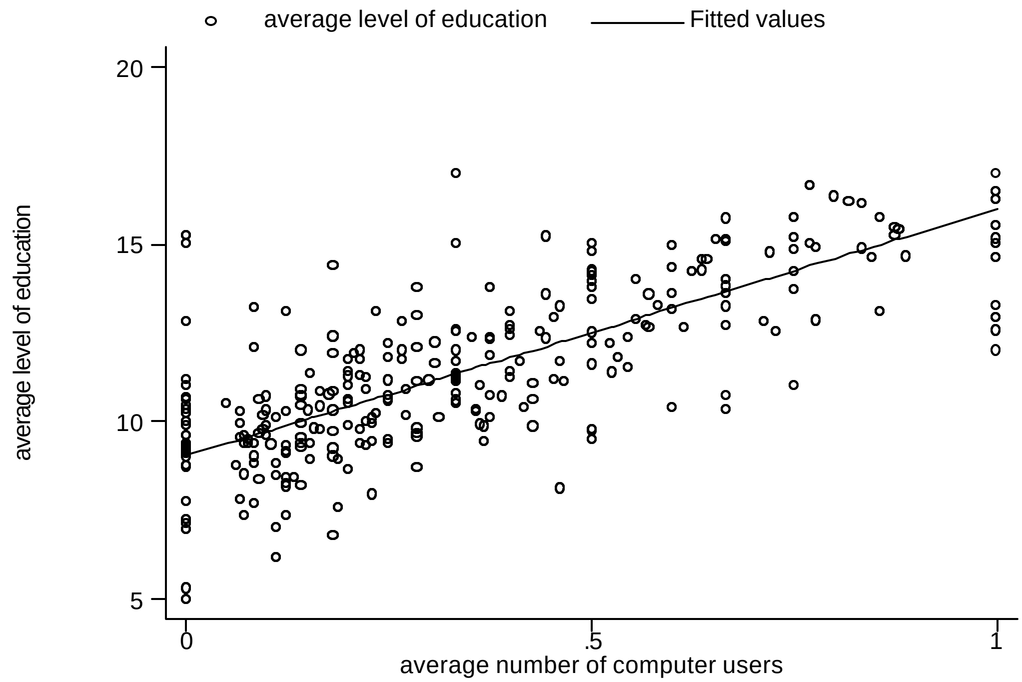
In the graph below we plot the regression line obtained from the regression of average number of computer users against the average level of education calculated as the average of each geographical neighbourhood.

[13] In this context the geographical neighbourhood is defined as the *segmento*.

[14] The correlation between use of computers and level of education drops below 0.5 if calculated at the individual level.

Figure 6. Use of Computers and Years of Schooling at *segmento* Level

(Full time Employees aged between 14 and 65)



The correlation between the log of the wage and use of computers (again, as the average of each geographical neighbourhood) is also very high, reaching an approximate level of 0.75. This high level of correlation corroborates the assumption that neighbourhoods are particularly homogeneous environments: rich neighbourhoods are those with the highest number of computer users and with the highest average level of education. This evidence suggests the existence of strong *segregation* between rich and poor neighbourhoods. This phenomenon would require more profound investigation, which is beyond the scope of this paper.

4.2 MAIN RESULTS

In this section we will present the main results obtained from the model estimation. The reference model is the one developed and discussed in section 3. In this model there are three independent variables that aim to explain the dynamics of logarithm of wages (the dependent variable). The three independent variables are: E_i (years of schooling), $m_n = E_i \frac{\sum_{j \in n} E_j}{N-1}$, and $v_n = D_n m_n$. As already explained m and v represent respectively the contribution to returns to knowledge given by the surrounding neighbourhood in which each person interacts, and the returns to connectivity expressed as access to ICT. Looking at the structure of the three independent variables, some problems of multicollinearity might be expected to arise[15]. This is due to the way in which m and v are constructed (i.e. v is a function of m and both are functions of E_i). To avoid this problem we need to use some other variables that can proxy m and v without generating multicollinearity. The two most obvious candidates are $\frac{\sum_{j \in n} E_j}{N-1}$ and D_n. To be sure that these are good proxies we look at the correlation index between m and v and their proxy variables. We do this for all surveys used and at all definitions of neighbourhoods considered. In table 5 are the correlation coefficients referring to the year 1998. The high level of correlation between the variables considered suggests that the proxies chosen will allow us to overcome the multicollinearity problem without losing much information.

Table 5. Correlation coefficients

	Encuesta de Ocupación		Encuesta CASEN		Encuesta SIALS	
	m	v	m	v	m	v
$\Sigma_{segmento}$	0.8393		0.8886			
$D_{segmento}$		0.9155		0.8485		
Σ_{comuna}			0.6668			
D_{comuna}				0.8356		
Σ_{work_net}	0.9327		0.9028			
D_{work_net}		0.9139		0.8537		
$\Sigma_{social-affinity}$					0.8170	
$D_{social-affinity}$						0.9202

Source: CASEN 1998, Encuesta de Ocupación y Desocupación 1998, SIAL 1998.

[15] It indeed arose in several preliminary regressions.

In the light of this observation we can rewrite the model to be estimated as follows:

$$\ln W_i = a + bE_i + b_1 \frac{\sum_{j \in n} E_j}{N-1} + b_2 D_n + e \qquad (10)$$

As already mentioned, we estimated several versions of equation (10), using different databases, different regression techniques (i.e. regular OLS model and Heckman selection model[16]), and finally, different definitions of neighbourhoods (i.e. *geographical neighbourhoods* and *social neighbourhoods*).

One possible problem associated with our definition of geographical neighbourhood is the presence of endogeneity in the relation between the neighbourhood's average level of education and individual wage. This is a common problem of the literature on peer effects which follows from the possible presence of self-selection mechanisms to join various groups. "Neighbourhood … composition reflects the constrained choices of their members, so that identification of group effects may be difficult to disentangle from individual characteristics" (Durlauf, 1997). In our case the causality nexus could go from average level of education to wages, and therefore support our hypothesis of interactive learning, as well as from individual wage to average level of education (suggesting that richer people move from poorly educated neighbourhoods to better off neighbourhoods). One way to control for this endogeneity problem would be to set up a simultaneous equation model, which would allow us to redefine the neighbourhood variables by means of instruments[17]. Unfortunately, the data available do not allow us to define reliable instruments. Therefore we control the problem of endogeneity by means of comparison of the results with different definitions of neighbourhoods. In this regard it is extremely important to have both social and geographical neighbourhoods.

All results obtained are consistent and tell the same story: introducing the network variables in the Mincerian regression generates a sharp reduction in the impact of schooling on the wage (generally estimated around 12%). Moreover, the returns to the neighbourhood's level of education and the returns to connectivity have the expected positive (and significant) coefficients, suggesting that both variables have a positive and significant impact on wages. In other words, the neighbourhood level of

[16] For a complete discussion on the Sample Selection Model see Heckman (1979).
[17] Technically this problem is solved using TSLS estimations.

education, and the neighbourhood average level of access to computers or telephone lines, affect positively the individual level of wages. This result confirms the importance of interactive learning in determining wage dynamics.

We have estimated several models with robust OLS. Since the observations are independent across groups (neighbourhoods) but not necessarily independent within groups (due to the presence of repeated observations on individuals) we controlled our estimators using the cluster option available in the econometric packet STATA. In table 6 below, we report a summary of the main results of the model estimated with the *Encuesta de Ocupación y Desocupación*, the CASEN survey and the *International Adult Literacy Survey*. We present four models, all variants of the model presented in equation (10). The first model uses geographical neighbourhoods defined as *segmento*; the second model uses geographical neighbourhoods defined as *comuna*; the third model uses social neighbourhoods defined as the work environment; finally the fourth model uses social neighbourhoods defined as social-affinity neighbourhoods. Each model has been estimated with different databases. Not every model has been estimated with all databases due to the databases' characteristics.

Table 6. Full time workers aged between 14 and 65. Dependent variable: log of wage.

	Robust OLS estimators					
	EOD, 1998		CASEN, 1998			IALS, 1998
E_i	*0.047***	*0.0324***	*0.046***	*0.0858***	*0.0438***	*0.0718***
$\Sigma_{segmento}$	*0.1038***		*0.0852***			
$D_{segmento}$	*0.0043***		*0.0034***			
Σ_{comuna}				*0.0895***		
D_{comuna}				*0.0028***		
Σ_{work_net}		*0.0897***			*0.0827***	
D_{work_net}		*0.0031***			*0.0053***	
$\Sigma_{social-affinity}$						*0.0377***
$D_{social-affinity}$						*0.0039**
Constant	*10.2144***	*10.6148***	*10.3172***	*9.8821***	*10.2768***	*12.9026***
R-square	*0.4606*	*0.4143*	*0.4267*	*0.3755*	*0.4389*	*0.2533*

Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better. ** = significant at 1% or better.

The results, independently from the definition of neighbourhood adopted, confirm quite strongly the presence of a significant neighbourhood effect. All variables considered are statistically significant and have the expected sign. The effect of returns to schooling varies between 5 and 8 percent according to the definition of neighbourhood[18]. This finding confirms our expectation of a traditional over-estimation of the returns to individual learning. The return to neighbourhood interaction is always significant and ranges between 4% and 10%. It is important to observe that the importance of interactive learning drops markedly when considering social-affinity neighbourhoods, but it keeps the expected sign and its statistical significance. This is probably due to the fact that when using social-affinity neighbourhoods, we minimise the statistical effect of self-selection.

The coefficient of the connectivity variable is around 0.004, meaning that an increase of one percentage in the use of computers density (where a density of 100% means that all people resident in a specific neighbourhood have access to computers) generates an increase of 0.4% on the dependent variable. This result is consistent through the different definitions of neighbourhoods.

In conclusion, we can assert that the results obtained consistently confirm our core hypothesis that the interactive phase of the learning process plays an important role in explaining the wage dynamics. If we do not consider the *neighbourhood effect* we risk overestimating the impact of individual learning.

The second hypothesis of our model was the occurrence of a poverty trap triggered by the different abilities to gain from interactive learning according to the different levels of individual learning (i.e. years of schooling). To address this question we estimated the model reported in equation (10) for different levels of education. We first calculate the return to individual and interactive learning for individuals who have completed only primary school, then for individuals who have completed secondary school, and finally for individuals who have university levels of education[19].

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18 When the neighbourhood is defined as *segmento* or work environment the return to schooling is approximately 0.45; on the other hand when considering larger neighbourhoods (*comuna*) the return to schooling is almost twice as large.

19 A problem associated with these regressions is the small number of people in each neighbourhood when the overall sample is split into three sub-samples according to the level of education. This problem is not present in the case of the CASEN survey, when the neighbourhood is defined at *comuna*

Table 7. Results from the *Encuesta de Ocupación y Desocupación*

	Encuesta de Ocupación y Desocupación					
	Less then 7 years of schooling	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*	*Less then 7 years of schooling*	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*
E_i	*0.0236**	*0.0507***	*0.1606***	*0.0318***	*0.02731***	*0.1231***
$\Sigma_{segmento}$	*0.0113*	*0.0379***	*0.0832***			
$D_{segmento}$	*0.0009*	*0.0044***	*0.0052***			
Σ_{work_net}				*0.0081*	*0.0195*	*0.1176***
D_{work_net}				*0.0009*	*0.0031***	*0.0066***
Constant	*11.4401***	*10.8273***	*8.8472***	*11.525***	*11.3374***	*8.5792***
R-square	*0.0195*	*0.1353*	*0.4240*	*0.0288*	*0.0958*	*0.3874*

Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better. ** = significant at 1% or better.

Table 8. Results from the *Caracterización Socioeconómica Nacional* (CASEN)

	Enquesta CASEN								
	Less then 7 years of schooling	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*	*Less then 7 years of schooling*	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*	*Less then 7 years of schooling*	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*
E_i	*0.0113**	*0.0291***	*0.1454***	*0.0256***	*0.0636***	*0.1962***	*0.0192***	*0.0345***	*0.1273***
$\Sigma_{segmento}$	*0.0396***	*0.0635***	*0.1046***						
$D_{segmento}$	*0.0035***	*0.0033***	*0.0039***						
Σ_{comuna}				*-0.0086*	*0.0319***	*0.1135***			
D_{comuna}				*0.0081***	*0.0055***	*0.0012***			
Σ_{work_net}							*0.0297***	*0.04933***	*0.0644***
D_{work_net}							*0.0067***	*0.0057***	*0.0085***
Constant	*11.0002***	*10.6412***	*8.5406***	*11.1184***	*10.4936***	*8.0711***	*10.9201***	*10.6386***	*9.0509***
R-square	*0.1410*	*0.1875*	*0.3343*	*0.1102*	*0.1171*	*0.2848*	*0.1631*	*0.1809*	*0.3163*

Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better. ** = significant at 1% or better.

level, as we still have large neighbourhoods. The fact that this result is consistent with all the other results allows us to underplay the impact of this limitation.

Table 9. Results from the *International Adult Literacy Survey*

	International Adult Literacy Survey					
	Less then 7 years of schooling	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*	*Less then 7 years of schooling*	*Between 7 and 12 years of schooling*	*More than 12 years of schooling*
E_i	-0.0232	0.0859**	0.1857**	-0.0158	0.1119**	0.1847**
$\Sigma_{social-affinity}$	0.0898**	0.0148	0.0422	0.0853**	0.0041	0.0383
$D_{social-affinity}$	0.0005	0.0055*	0.0009	0.0050	0.0067**	0.0009
Experience					0.0626**	0.0422**
Experience sq.					-0.0010**	-0.0010**
Constant	12.993**	12.903**	11.2584**		12.0265**	11.0182**
R-square	0.0617	0.0836	0.1392	0.0678	0.1503	0.1509

Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better, ** = significant at 1% or better.

First, from this analysis we confirm that the Chilean labour market is characterised by increasing returns to schooling. Secondly, we notice that higher levels of individual learning generate higher returns from interactive learning. In the tables above we summarise these results[20].

The first two sets of results confirm our hypothesis of cumulative effects between individual learning and interactive learning, suggesting that those people who have a high level of schooling will be able to gain the most from interactive learning. Putting it in other words, this result confirms the assumption that a *poverty trap* exists, generating divergence between skilled and unskilled labour. The results obtained with the *International Adult Literacy Survey* are inconsistent and mostly insignificant. This is probably due to the smaller number of observations available in this database.

4.3 CONTROLLING FOR THE ROBUSTNESS OF RESULTS

The results obtained so far are consistent and robust throughout the model specifications considered. It might be argued, though, that these model specifications

[20] Table 8 reports only the results concerning the OLS estimations and aggregated at *segmento* level. When running the Heckman selection model we however obtain very similar results. Moreover, the level of aggregation does not affect the outcome. More detailed results are available from the author.

do not take into account other variables usually included in the returns to schooling literature. In order to tackle this objection we controlled for the presence of omitted variables, which could generate biased coefficients. We developed a wider specification of the model which includes all the variables usually used in the literature, and tested the stability of our parameters. In one model estimation we also included a dummy variable called *Discrimination*. This variable assigns a value of 1 to those districts that appear to be particularly rough[21]. The reason we introduce this variable is because the Chilean labour market appears to be heavily affected by discriminatory behaviour (i.e. people resident in poor and rough neighbourhoods have fewer chances to get a good job as opposed to people resident in better-off districts). This marked distortion might affect the meaning of our neighbourhood variables, capturing a discrimination effect rather than the true effect. The introduction of this new dummy variable, however, does not change our results substantively. In fact, the variable is statistically not significant.

Table 10. Summary of different models specification. (Robust OLS estimators)

	Caracterización Socioeconómica Nacional					
	Robust OLS estimators					
E_i	*0.046***	*0.0858***	*0.0438***	*0.0706***	*0.0966***	*0.0698***
$\Sigma_{segmento}$	*0.0852***			*0.0507***		
$D_{segmento}$	*0.0034***			*0.0029***		
Σ_{comuna}		*0.0895***			*0.053***	
D_{comuna}		*0.0028***			*0.0031***	
Σ_{work_net}			*0.0827***			*0.070***
D_{work_net}			*0.0053***			*0.0048***
Experience				*0.0215***	*0.0242***	*0.0245***
Experience sq.				*-0.0002***	*-0.0002***	*-0.0002***
Constant	*10.3172***	*9.8821***	*10.2768***	*10.1278***	*9.7784***	*9.8152***
R-square	*0.4267*	*0.3755*	*0.4389*	*0.4170*	*0.3971*	*0.4816*

Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better. ** = significant at 1% or better.

[21] The selection of these rough districts was made through the use of interviews with residents of the Great Santiago area.

The table above reports a summary of the results obtained with different model specifications for the CASEN survey[22]. In all the cases the coefficients of the neighbourhood variables are correctly signed, statistically significant and of similar magnitude to those reported in table 6.

As already mentioned, a second objection which might be raised with regard to our model is the presence of selection bias. In order to control for this potential shortcoming we have re-ran all the different specifications of our model using the Heckman selection procedure. In all cases the results were consistent with the OLS robust estimators. Below we report a summary table for the CASEN survey[23].

Table 11. Summary of different model specifications (Heckman selection model)

	Caracterización Socioeconómica Nacional					
	Heckman selection model					
E_i	*0.0461***	*0.0859***	*0.0438***	*0.0706***	*0.0966***	*0.0699***
$\Sigma_{segmento}$	*0.0851***			*0.0507***		
$D_{segmento}$	*0.0034***			*0.0029***		
Σ_{comuna}		*0.0896***			*0.053***	
D_{comuna}		*0.0027***			*0.0031***	
Σ_{work_net}			*0.0828***			*0.0698***
D_{work_net}			*0.0053***			*0.0048***
Experience				*0.0215***	*0.0242***	*0.0246***
Experience sq.				*-0.0002***	*-0.0002***	*-0.0002***
Constant	*10.3202*	*9.8849*	*10.2786*	*10.1278*	*9.7784*	*9.8106*

Selection Mode: sex, age, sq. of age, experience, sq. of experience.
Notes: Unstarred variables are not significant at the 10% level. * = significant at 10% or better. ** = significant at 1% or better.

5. Conclusion

The core message of this paper is that building human capital is a complex process based on formal education (i.e. schooling and training), as well as on interaction with other people. In modern societies almost everybody has the chance to acquire a minimum level of education through the formal system of schooling. Nonetheless, the

[22] Similar summary tables of the other two databases are available from the author.

social groups within which people interact in their daily life are very different. This kind of informal interaction can be seen as a process of knowledge exchange, which takes place through face-to-face interaction. In this work we have tried to measure the impact of both kinds of learning mechanisms on the wage dynamics. We called these two phases (faces) of human capital creation individual learning and interactive learning.

There are two main results of this investigation: first, interactive learning is as important as individual learning in determining wage dynamics; second, the higher is the level of formal education (schooling) the higher will be the returns from interactive learning. On average, a person with more than twelve years of education will gain twice as much as a person with less than seven years of schooling. These findings suggest the occurrence of self-reinforcing mechanisms, which generate a vicious circle for those people who are initially endowed with low levels of formal education, and a virtuous circle for those endowed with high levels of education. The cumulative effect of this twofold dynamic is the increase in wage inequality as well as the polarisation of the society.

A first policy implication that follows these findings is that measures taken to reduce inequality should focus on the redistribution of neighbourhoods' membership. Durlauf (1996, 1997) calls this policy 'associational redistribution', and shows how in many cases government policy of this type has contributed to the reduction of inequality in the USA. Indeed, in the case of Chile, this kind of policy is particularly needed since the society displays high level of inequality coupled with high level of segregation. A governmental policy of neighbourhood membership redistribution would facilitate interaction between people from different social classes and therefore would facilitate an equal diffusion of knowledge boosted by informal interactions. This policy should be coupled with substantial investments in education aimed at increasing the absorptive capacity of people. The combination of theses two policies would maximise the interactive learning impact.

[23] More detailed results are available from the author upon request.

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