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Wages and Workplace Computer Use in Chile

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Abstract

This paper presents robust evidence regarding the impact of computer use at the workplace in Chile for the period 2000-2006. The main contribution is to present evidence in a developing country using matching techniques, assuming a homogeneous treatment effect. Wage impact is then measured through the nearest neighbor and kernel estimator. Results consistently show that there is a premium associated to the use of computers at the workplace, which is interpreted as an increase in the person's productivity derived from the inclusion of an additional production factor, i.e. the computer. All of this is consistent with a model where penetration of computers decreases this premium, something that actually has occurred in Chile during this period. In effect, the estimates show a premium about 26% for 2000 but in 2006 it goes down to 16%.

Keywords: Computer, Impact evaluation.

JEL Classification: C14, J24, J31.

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1. Introduction

One of the economic issues that have captured most attention in recent decades relates to the impact of individual characteristics on wages. The traditional Mincer equations, based on human capital theory, even allow the return on individual education to be differentiated (Jaeger and Page, 1994). The covariates normally used in the empirical specifications include schooling or some variant of the same to capture returns differentiated by educational cycle, and potential experience that captures the income profile of person's life cycle. Over time, and as new issues have arisen regarding elements that could be behind the determination of salaries, additional variables have been included, such as gender, in order to capture discriminatory behavior in the labor market (Hamermesh, 1994).

Technological changes are another important factor in wage determination (Acemoglu 1998, Autor *et al* 1998 and 2001, Card and DiNardo 2002, Freeman 2002, Katz and Murphy 1992, Krueger 1993). While it may well be difficult to measure said changes in determining the way in which it affects wages, there are some indicators that appear to be associated to those changes. One of these indicators is the use of computers in the workplace. In effect, development of the computer could have a major impact in terms of labor productivity given that it improves performance in various production areas (Autor *et al* 2001, Bresnahan 1999). Therefore, analyzing the impact of the use of this technology on the economy and, specifically in wage structure is of great interest. Earlier studies in this area have extensively documented the impact associated to the use of computers in the workplace; however, there has been less discussion on why the use of such technology may impact individual wages.

Why does someone use a computer at work? The simplest and most logical answer seems to be because the company where they work has and uses computers. The next question would be why do companies provide computers in their economic activity? In other words, why does the company supply its employees with computers? If we consider companies to be maximizing organizations, then the answer is clear: they use computers because it is profitable to use them. Since computers cannot operate themselves, someone has to take charge of them. Therefore, it is the individual that uses the computer.

The traditional manner of estimating the impact of computer use at work on labor income is by including a dummy variable that indicates whether a person uses or does not use a computer at work. While this simple method of broaching the problem may be illuminating, it shows certain weaknesses. Specifically, it has the same problem as all wage equation estimates, that is, the impossibility of controlling the individual's ability, which would lead to inconsistent estimates of the true impact of computer use. In other words, it is possible that individuals who use computers at work may be individuals with higher abilities on average. This is a serious problem and, the interpretation of the estimated coefficient associated to the dummy variable mentioned above is not clear. Nevertheless, Krueger (1993) presents solid evidence that the return associated with computers use is not greatly affected by the omission of individual ability. On the other hand, and sadly, individual ability information is not always available. However, OLS imposes strong functional assumptions to estimate the impact of computer use in the workplace. That's why we move on to the matching techniques, which is a nonparametric version of least squares that does not impose functional form assumption on outcome equations. Besides matching focus on individual that are more similar through the common support condition.

Therefore, two levels of estimates of such impact are carried out. Firstly, and following the available literature (Krueger 1993, Bravo *et al* 1999) a dummy variable indicating whether individual uses a computer at work or not is included in a Mincer equation. Secondly, the use of computers at the workplace is analyzed through matching technique (Heckman *et al* 1997, 1999). Based on the conditional independence assumption we treat the use of computer as random with respect to the outcome.

But, why is Chile an interesting case of study? There are several reasons. First, Chile is an economy moving from underdevelopment to be a developed economy, and future growth will be sustained more and more on skilled labor. Hence, the use of computer will encourage this dynamic and it is very interesting to determine what the effects will be. In fact, Bresnahan *et al* (2002) find that incorporation of IT (information technology) in USA caused a skill biased technological change. Also, given this kind of knowledge (using a computer) may diffuse more easily among population the return associated to the use of computer at workplace could be wide enough. Second, and related to the previous one, to quantify the effect of technological change on productivity is always interesting to investigate, and the use of computer in the workplace represent a measurable dimension of the effect that has had this change. In effect, Bartel *et al* (2007) provide robust evidence about the positive effect of IT on productive process of firms in United States. Third, it is interesting to study the Chilean case because Chile is an economy with a high degree of income inequality; in fact, it is one of the more unequal country in the region. Given technological change complements highly skilled labor (Krueger, 1993) then computer use will affect the relative wages probably increasing this high inequality.[2] One last reason to analyze this economy is the availability of micro data; the CASEN (encuesta de Caracterización Socioeconómica Nacional) is a cross section survey with national representation and it is a fundamental tool for social policy because it contains valuable information of the Chilean families regarding housing, education, health and labor characteristics. Besides, it included for 2000 and 2006 years a couple of questions that make possible to get information relative to the access and frequency use of a computer in workplace.

The OLS and matching estimators reveal a significant effect of using a computer at workplace in Chile. Assuming a homogeneous treatment effect and selectivity based on observables, the impact is around 26% in 2000 and 16% in 2006.

The paper is structured as follows. Section 1 contains this brief introduction. Section 2 presents a theoretical discussion regarding the wage impact of computer use at work. Section 3 presents national and international evidence regarding the returns associated to computer use. In section 4, there is an analysis of the data and of the determinants of computer use at work in Chile. Section 5 presents the parametric and non-parametric estimates of the returns. Finally, section 6 presents the main findings.

2. Returns on what and why?

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[2] Official records indicate that GINI coefficient of household income is about 0.54.

As shall be discussed hereafter, there is a robust body of documentation available both nationally and internationally, on the existence of a return associated to computer use at work.

Before discussing these results, it is worth asking why such a return exists, and in effect, what does it mean? This discussion has not been exhausted in the available literature.

Hypothesis of a technological change biased in favor of skilled labor has been widely used to explain why demand for skilled labor has increased in recent years (Card and DiNardo 2002, Autor *et al* 2001). In turn, this provides a theoretical foundation for the observed increase in relative wages of the most highly skilled workers.[3]

In effect, to simplify the discussion, one may conceive a labor market with only two types of workers, skilled (C) and non-skilled (NC). Let r be the ratio of wages between both types of workers (W_C / W_{NC}), and let p be the ratio between the number of skilled and unskilled workers (L_C / L_{NC}).

For the sake of simplicity, it is assumed that the relative supply of skilled workers is inelastic. A negative slope curve represents the relative demand for skilled workers. The slope is negative since the lower the r, the cheaper the skilled workers in relative terms. Figure 1 shows the above mentioned situation.

Initially, the market finds its equilibrium in point A. Under these conditions, there are only two ways in which wage inequality between both groups of workers can increase. The first is given by a shift to the left of the relative supply of skilled workers, which would increase their relative wage. Alternatively, this could occur due to an increase in the relative demand for skilled workers.

Nevertheless, the evidence for Chile consistently shows an increase in the relative supply of skilled workers (Bravo *et al* 1999). If this were the whole story, then the economy would

[3] Katz and Murphy (1992) present evidence for the United States and Bravo *et al* (1999) does for Chile.

shift to point *B* of Figure 1 (S_1), whereby the relative salary of skilled workers would decline, a situation that has not occurred in Chile.

Apart from the increase in the relative supply of skilled workers, a sharp increase in the demand for skilled workers have been recorded, this is graphically shown by a shift to the right in the labor demand curve (D_1). The new equilibrium point in the economy is given by point *C* of the figure, with a higher relative salary level of skilled workers.

But what can such a sharp shift in the demand for skilled workers be due to? The hypothesis of a technological change biased in favor of skilled labor provides an answer.

As is indicated in various studies (Griliches 1969, Acemoglu 1998), physical capital substitutes skilled labor less than it does unskilled labor, or in other words, capital complements skilled labor more than it does unskilled labor. If technological change is defined as a change in the curvature of the production function, due for example, to the introduction of computers, there are grounds for suspecting that this fact will trigger an increase in the relative demand for skilled workers in the measure that it increases the relative marginal productivity of skilled workers. Figure 2 shows the consequences of this situation on relative wages and employment. The firm is initially in equilibrium in point *E* with a factor ratio use between skilled (*C*) and unskilled workers (*NC*) given by the slope of ray *0Q*. A technological change biased in favor of skilled labor, which may be seen as the introduction of computers at work, will alter the factor ratio use in the measure that it is more complementary with skilled workers (*C*) than with unskilled workers. The firm will now be in point *F* of figure 2 with a new factor ratio use given by the slope of ray *0P*.

However, it is worthwhile asking why the new technologies complement the most skilled workers. Acemoglu (1998) shows why most new technologies are complementary with skilled labor by means of a model in which the direction of the technological change is endogenous. The author argues the following: once developed, most technologies are non-competing goods. They may be used by different firms and workers at low marginal costs. The higher the amount of skilled workers, the greater the market for complementary technologies with the said workers. In this way, the inventor shall have greater possibilities of obtaining benefits and will, therefore, dedicate a greater effort to the invention of technologies that are complementary to skilled workers. This effect of market size is crucial for deriving the main conclusion from such work which is, that the increased supply of a given factor may lead to a greater investment in technologies that are complementary to the said factor. This is precisely what is argued, for the purposes of the present paper. In other words, the increase in the supply of skilled labor in recent decades has led to a deep penetration of computers at the workplace, furnishing workers with better technologies and determining an increase in labor productivity.

The effect of technological change biased in favor of skilled labor on wage distribution in the United States for the period 1940 to 1996 is analyzed in Autor *et al* (1998). The interesting aspect of that work is that it measures technological change through computer penetration in the labor market. Specifically, the authors find that more computer-intensive industries have experienced a greater increase in the demand for skilled labor.

Estimates with cross-section data and with longitudinal data are carried out in Doms *et al* (1997) to determine the relationship existing between technology and skill level of workers. The authors find mixed evidence. While the cross-section information is consistent with earlier results from other authors, the result obtained using longitudinal information is less conclusive.

Finally, how computer use alters the demand for skilled workers is analyzed in Autor *et al* (2001). Firstly, the authors define the potential functions of a computer. They argue that a computer basically carries out very structured tasks using a rule-based logic. In other words, there are functions that simply a computer cannot carry out. This is the central point argued by these authors.

For simplicity's sake, two types of tasks may be identified, routine and non-routine. The routine tasks are those that can be codified through a well-structured manual and do not require particular skills, in other words, they can be carried out by a computer. On the other hand, non-routine tasks are those that require manual as well as visual abilities to execute them and, therefore, cannot be carried out by a computer. This model is discussed in further detail in the following section and shall serve as the theoretical foundation for the estimates that shall be carried out further ahead regarding the impact of computer use at the workplace on wages.

3. Evidence

The model presented above provides well-grounded reasons for believing in the existence of a positive return associated to computer use at the workplace which is decreasing when computers penetration increases. In any case, if this were not so, what would be the reason that would explain why companies have experienced such a dramatic computerization process? Krueger (1993) appears as the pioneering work in this area, where the wage impact for an individual using a computer at work is evaluated. To evaluate this hypothesis, this author uses data from the Current Population Survey (CPS) for the United States and estimates the following model by ordinary least squares (OLS):

$$y_i = x_i'\beta + \alpha C_i + u_i \tag{1}$$

where C_i is a dummy variable with the value of one if individual i uses a computer at the workplace and zero if not. Vector x_i' includes characteristics of the individual as well as of workplace. This author finds a return of 27% associated to computer use for the year 1984, which declines to 14% when other individual characteristics such as production sector and gender are controlled for. The author finds a return of 32% for the year 1989, which drops to 16.2% when other factors are controlled for.

However, the problem that arises with this type of estimates is the omission of relevant variables. It is possible that computer users possess abilities that are not observable to the researcher. These abilities could be determinant in whether an individual uses a computer or not. To face this potential problem, the author suggests four alternative strategies: (1) Controlling computer use at home, (2) carry out estimates by types of profession in particular, for example secretaries, (3) using information available from results of individual's ability tests and thereby controlling abilities, and (4) estimate in differences by type of occupation to control possible fixed effects.

The above mentioned strategies can be broken down into two groups. The first group attempts to measure directly and includes ability in the impact estimates. Meanwhile, the second group of estimates tries to avoid the problem by allocating the estimates into subsets of individuals, in which the ability distribution should have a lower dispersion. The omitted variable, thereby does not introduce so much noise into the estimates. After implementing all of these strategies in the estimates, the author still finds significant pecuniary returns associated to computer use at work.

Later, in a provocative work, DiNardo and Pischke (1997) establish that actually the supposed returns on computer use simply reflect differences in the incomes of individuals not captured by other variables in the model. In effect, using labor data from Germany and estimating a similar equation to (13) through OLS, they find positive and statistically significant returns of around 15% on computer use at work. However, through a similar analysis, they establish positive returns in the use of telephones and even pens. They basically propose that the returns found with this type of tool simply constitute a proxy of the wage structure in an economy.

In the case of Chile, Bravo *et al* (1999) evaluates the impact of computer use at work using two sources of information: Employment and Unemployment Survey of the Universidad de Chile and the Second International Adult Literacy Survey (SIALS). In both cases, the group under analysis is made up of salaried and full-time male workers. Using the employment survey, the authors find a return associated to computer use of around 35% after controlling by other individual characteristics. However, when the literacy survey is used, a return of between 28% and 32% is reported.[4] With this result, the authors conclude that there is a premium to computer use in Chile and that it is independent of abilities and characteristics of the workers.

[4] The objective of using the second database lies in the possibility of controlling for the ability of individuals, since this survey contains information referring to the results of the tests applied to the workers, which can be used as proxies for ability. Surprisingly, the estimated coefficient of returns on computers did not vary.

What justifies estimate the impact of computer use in this way? This is important in order to understand what are estimating. Consider the following: it is possible to think of the decision of using a computer at work as a latent variable that is influenced by a vector of characteristics (Z), such as:

$$C_i^* = Z_i'\gamma + v_i$$

where C_i^* is a latent variable that is not observed by the researcher. One observe whether the individual uses or does not use a computer at work, C_i, which is a dummy variable.

Let Y_1 be the wage per hour of the individual that uses a computer at work and let Y_0 be the wage per hour of the individual that does not use a computer at work. Then:

$$Y_0 = \mu_0 + U_0$$
$$Y_1 = \mu_1 + U_1$$

The econometrician observes:

$$Y = CY_1 + (1 - C)Y_0$$

Rewriting this expression:

$$Y = Y_0 + (Y_1 - Y_0)C$$

Assuming the case of homogeneous treatment effect ($U_0 = U_1 = U$):

$$Y = \mu_0 + (\mu_1 - \mu_0)C + U$$

The least squares approach permits identify the average treatment effect (ATE) assuming that there are not differences in non observables. In fact, in this context all of the treatment parameters are equal:

$$ATE = TT = TUT$$

Given the selectivity you can control by Z, and you can get the impact of using computer at workplace through OLS, but also we are assuming a specific functional form on the outcome equations. So, the logical next step would be relaxing this assumption enabling a nonparametric version of this impact. That's exactly what matching actually does.

4. Data

To estimate the impact of computer use at work the CASEN Survey (National Socioeconomic Characterization Survey) was used for 2000 and 2006. CASEN is a cross section survey with national representation and it is a fundamental tool for social policy in Chile because contains valuable information of the Chilean families regarding housing, education, health and labor characteristics. Those years were chosen since they included a couple of questions that permit identifying in a virtually direct manner those individuals who use computers at work. Specifically, the questions that permit to determine whether a person uses a computer at work regularly are as follows: *Do you have access to a computer? Where do you have most frequent access to a computer?* Thus, individuals who answered the first question affirmatively and additionally indicated that they have most frequent access to computers at work were categorized as workers who use computers at work ($C = 1$). It is worthwhile noting that, given the availability of data, this is the best way to determine whether a person uses a computer at work or not.[5]

Thus, despite having cross-section information (for two years), this survey has the advantage of being representative at a national level, which additionally includes a wide spectrum of individual employee characteristics. In order to focus on estimating the returns on the use of computers and avoid other types of problems, the sample shall be restricted to men, white collar and blue collar workers, working fulltime, as in Bravo and Contreras (2001), and Bravo *et al* (1999).

Table 1 presents some characteristics of the individuals surveyed separated by those who indicate having a computer at work and those who indicated that they did not. There are

[5] This situation must be kept in mind when making comparisons with earlier studies.

significant differences by groups, revealing that using a computer is affected by several characteristics. As can be noted, these differences remain stable in time.

Table 2 present other additional variables for both groups of individuals. It may be said that, on average, individuals who use computers at work earn more, have more schooling and have less work experience.[6] Furthermore, it may also be observed that pay differences are significant. In effect, year 2000 data shows that those individuals who use a computer at work have an average hourly wage of CLP $2,109, while the average pay per hour for those that do use computers barely reaches CLP $1,089, and this gap keeps on 2006 year data. Workplace computer users in CASEN 2006 have an average hourly salary of CLP $2,471, while the non user of computer at workplace reaches CLP $1,250. Upon analysis of the data, two interesting aspects appear that should be highlighted. One of these relates to the age of the person. The previous tables clearly show the fact that new technologies are more likely to be used by young people. The other important aspect relates to the schooling of individuals. People who use a computer have more schooling. In the context of this study, this indicates that more skilled workers have more abilities in carrying out non-routine tasks.

Even though individual characteristics such as age and level of schooling may be related to the probability of a worker indicating that he/she uses a computer at work, it may also be the case that characteristics of the firms where these individuals work may also affect such probability. In fact, they may well be the most important factors. In effect, the results of a probability model (presented in Table 3), suggest that variables associated to the size and productive sector of the firm are as important as the individual variables. In both tables results show a positive relationship between the size of a firm and the probability of having computers. Meanwhile, employees in more information technology intensive sectors, such as the financial sector, have a higher probability of reporting computer use in the office than those in more unskilled labor intensive sectors such as the construction industry.

[6] Potential work experience is used, defined as: age - schooling - 6.

Taking into account all of the aforementioned, one may consider the possibility of directly modeling the decision of using a computer at work. According to data presented, all the variables included as controls in estimating the wage equation would be determining in the probability of using a computer. This would enable to us implement the matching estimators. The following section presents the estimates for determining the impact of using a computer at workplace.

5. Estimating Returns on Computer Use at Work

5.1 Parametric Estimates

The model developed in the present study suggests that people who use a computer are more productive since it complements their knowledge in carrying out non-routine tasks. Thus, the positive coefficient associated to the dummy variable that indicates whether a person uses a computer at work shows an increase in the labor productivity of an individual.

One of the main criticisms made about this type of estimates is that people who use computers are anyhow more productive (skilled), and therefore the coefficient associated to the dummy variable would simply be showing that differential. However, there are well-grounded reasons for thinking that computer use does not depend critically on individual ability (Krueger, 1993). Specifically, whether a person uses a computer at work or not, may depend directly on the company where they work, and not on the individual's productivity or ability. In fact, if it were so, firms would be segmented in terms of computer use. In other words, within a company, one does not find computers distributed in a non-uniform manner. Instead, one finds computerized or non-computerized companies; by computerized, we mean that their workers in general use computers. If the situation was not so, it would be worthwhile asking if there is some non-observable characteristics in the individuals that determines if these use or do not use computers at work. Why can the employer discern that characteristic?

Hence, the results presented in Table 3 on the probability of using a computer at work according to the characteristics of the company, would back to some extent the view presented here. Thus, when determining the probability of an employee using or not using a computer at work, the company characteristics are as important as the characteristics of the individual.

In this traditional estimating method, which is taken as a point of reference, vector x_i' includes a series of individual characteristics of the worker, such as schooling and potential experience.[7] Following specification (1), the vector of estimated parameters shows the impact of these variables on the salaries of individuals. Variable C_i indicates whether a person uses or does not use a computer at work, and therefore α shows the impact of computer use at work on wages.

Tables 4a and 4b show the estimates under different specifications of the model. Column (1) shows the traditional estimate of a Mincer model. In 2000, the return on computer use at work is 21.5% and it is significant to 1%. In 2006, the return on computer use at work is 20.7%, significant to 1% too. Then, returns on workplace computer use has decreased by 0.8% between both years, what is coherent with the 2006 total computer users increase, in Table 1. Column (2) corrects for the region in which the employee works. In this case, the return on computer use at work rises to 21.6%, but for 2006 year, it decreases to 20.5% and it is again significant at 1%. Column (3) also controls the firm size. The return on computer use at work in 2000 is then 18.4% and it is similar for 2006 with 18.2% remaining significant at 1%. Finally, column (4) in both years also controls production sector where the individual works. The return on computer use here shifts to 17.9% in 2000 and to 18.1% in 2006 and it is significant at 1%.

As may it be observed, the results show a positive and significant return associated to the use of computers at work. It is also robust to different specifications. This return is in line with earlier studies in Chile (Bravo *et al* 1999, Bravo and Contreras 2001). While some

[7] Return on schooling has been differentiated according to educational cycle.

difference may exist, which is probably not statistically significant, the methodological differences present should be borne in mind.[8]

The OLS estimates identifies the impact of using computer in terms of earnings assuming a homogeneous treatment effect, that selectivity is based on observables, and that the outcome equations are well specified. This estimation identifies the average treatment effect, the treatment on the untreated (TUT), the treatment on the treated (TT) and all of them are equal. Next we present a matching version of this impact, which is a nonparametric way to estimate the effect of using computer on earnings. Therefore, we don't impose a functional form and we select the most comparable population through the propensity score. However, again treatment parameters are all the same.

5.2 Non-Parametric Estimates

Now, the matching estimators are implemented to evaluate a treatment that consists in an individual using a computer at work. The cross-section matching estimators are applied in the present study that compare the result (wage per hour) of the treatment and control groups at some moment in time subsequent to the implementation of the program. Two estimators area applied: the cross-section matching estimator of the nearest neighbor, and the kernel cross-section matching estimator.

In order to matching works we establish the following standard assumptions:

$$(Y_0, Y_1) \perp C \mid Z$$

$$0 < P(C = 1 | Z = z) < 1$$

The first condition randomizes *C* with respect to outcomes, and second assures comparing comparable people. The common support condition is also necessary.

5.2.1 Estimating a model that determines the probability of using a computer at work

[8] Basically refers to the construction of the dummy variable that indicates whether the individual uses a computer at work or not.

The first step consists of determining the propensity score or conditional probability of using a computer at work. Estimating this limited dependent variable model may be carried out parametrically as well as semi-parametrically. This estimate will allow the dimensionality of the determinants to be reduced to carry out the matching (Heckman 1999). To estimate the propensity score, a group of characteristics must be chosen as determinants. It is fundamental to restrict the choice to those variables that are not influenced by the program, but they were important at the moment when the decision was made. Otherwise, biased estimates shall be obtained regarding the true impact of the program.

Parametric Estimates

Table 5 show the estimated probability model and it may be observed that the greater the schooling, the greater the probability of using a computer at work. Meanwhile, the probability of using a computer at work increases at a declining rate with age. Finally, individuals from urban zones have a higher conditional probability of using computers at work. Besides of these variables, region, firm size, and economic sector dummies were also included.

Semi-Parametric Estimates

When a probability model is used to model a particular dichotomous decision, normalization tests must be carried out on the estimated residuals, in order to corroborate how well this structure adjusts to the underlying dichotomous decision. This is why normalization tests are carried out on errors from the estimated probability model. For this, the following specification is estimated:

$$C_i = Z_i'\gamma + Q_i'\delta$$

where $Q_i' = [(Z_i'\gamma)^2\ (Z_i'\gamma)^3]$. The estimated coefficients for Q_i' turn out to be significant, which indicates deviations from normality (the norm) in the errors. The estimates are shown in Table 6. The coefficients associated to the cube of the predicted probability are statistically significant. The estimated coefficients of the probability model are thereby inconsistent, which is serious for our present purposes given that this model has the task of assigning the experimental and control individuals with their nearest propensity score. We thereby proceed to carry out a semi-parametric estimate of the limited dependent variable model. It will be estimated semi-parametrically by means of the Klein and Spady method (1993).[9]

Table 7 shows the impact of the program by means of the matching estimators estimating parametrically the propensity score. As it may be observed, there is a premium associated to computer use at work. This premium may be observed consistently and through different techniques. In year 2000, this premium ranges from 23.7% up to 28.4%, while for year 2006 this premium ranges from 14.7% up to 19.6%. The results obtained show even a bigger impact related from using computer at work comparing to the traditional OLS estimates. So, using a computer at workplace pays.[10]

Besides, these results are consistent with the theoretical model. In effect, the penetration of computers in Chile has been enormous, consequently the marginal productivity of the workers assigned to non-routine tasks has increased significantly, which is related to the complementarities between routine and non-routine tasks. If the price of the computer diminishes their penetration in the various economic activities increases and consequently the premium associated for use a computer declines, something that has actually occurred in Chile.[11]

However, as earlier demonstrated, normality is rejected in the errors arising from the probability estimate of the limited dependent variable model. This explains why a semi-parametric estimate of the said model is implemented through the Klein and Spady method. Unfortunately, due to computer capacity limitations, it is not possible to carry out the said

[9] See appendix for details.

[10] An anonymous referee suggested to include in the probit model tenure and occupation of the worker. It is worth to note that results are robust to the incorporation of these variables. Although it would be interesting to add a variable controlling for intensity of computer use in workplace, with the information available that is not possible to do.

[11] Chile kept the highest grade of the Information Society Indicator in the Latin American Information Society. According to 2008 report Chile has 308 computers for each 1,000 persons being the leader in this area. This value represents an increase of 28% annual. This indicator is elaborated by Everis along with University of Navarra.

estimate (at least relatively efficiently) using the whole sample. Therefore, a sample was taken from the same, in order to carry out the estimate. Common support condition was imposed again. In order to assess if this sample is representative of the whole data, table 8 presents the impact estimates for this subgroup (10 percent). A return in line with the above may be observed. In fact, this return ranges from 18.6% up to 21.3%. This table also shows the impact using a *propensity score* that has been obtained semi-parametrically by means of the Klein and Spady method. Again, the existence of the return associated to computer use at work may be observed. The impact estimated is higher than previous ones but more uniform. Specifically, the return now ranges from 41.7% to 45.3%. This is interesting because the previous returns maybe were biased because of the probability model. So the matching could have been misleading since the propensity score variable for searching the clones was biased. But these results must be taken with precaution because it is a sample, not the whole database. Nevertheless, we have found a positive and robust impact computer use at the workplace in Chile which also is decreasing for the period 2000-2006.

6. Conclusions

Following Autor *et al* (2001), a model that allows a theoretical foundation for the premium associated to computer use at work has been presented. This associated return may be interpreted as an increase in worker productivity since the use of a computer allows them to complement their knowledge when carrying out non-routine tasks. Evidence from Bartel *et al* (2007) and Bresnahan *et al* (2002) supports this hypothesis.

The OLS and matching estimators reveal a significant effect of using a computer at workplace in Chile. Assuming a homogeneous treatment effect and selectivity based on observables, the impact is around 26% in 2000 and 16% in 2006 which is consistent with the theoretical model where penetration of computers decreases the premium for use a computer at the workplace.

Due to the presence of normality deviations in estimating the probability model, semi-parametric estimates of the propensity score are carried out, which show that the return found still holds but they are greater than the previous ones. This is interesting because the previous returns maybe were biased because of the probability model. So the matching could have been misleading since the propensity score variable for searching the clones was biased. But these last results must be taken with precaution because it is a sample, not the whole database.

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Table 1: Workplace computer use by people distinction distribution

	2000		2006	
	$C = 0$	$C = 1$	$C = 0$	$C = 1$
Total	86.54	13.46	85.87	14.13
By zone				
Rural	98.02	1.98	96.76	3.24
Urban	84.73	15.27	84.30	15.70
By Chilean geographic region				
I	85.79	14.21	88.07	11.93
II	84.94	15.06	88.77	11.23
III	86.39	13.61	85.70	14.30
IV	90.13	9.87	92.41	7.59
V	86.35	13.65	85.35	14.65
VI	92.26	7.74	90.04	9.96
VII	91.09	8.91	90.51	9.49
VIII	87.07	12.93	88.20	11.80
IX	88.69	11.31	88.72	11.28
X	89.85	10.15	86.51	13.49
XI	83.12	16.88	82.69	17.31
XII	82.00	18.00	79.17	20.83
Metropolitan Region	84.26	15.74	82.93	17.07
By age intervals				
18-25	89.38	10.62	89.16	10.84
26-35	82.45	17.55	81.31	18.69
36-45	87.06	12.94	83.26	16.74
46-54	88.01	11.99	88.94	11.06
>55	90.53	9.47	92.22	7.78
By economic activity type				
Not well-specified activities	66.46	33.54	70.82	29.18
Agriculture	97.31	2.69	97.19	2.81
Mining	82.31	17.69	82.04	17.96
Manufactures	87.07	12.93	86.49	13.51
Electricity, gas and water	75.25	24.75	82.36	17.64
Construction	93.94	6.06	93.62	6.38
Commerce	83.86	16.14	80.42	19.58
Transport and communications	88.59	11.41	88.25	11.75
Financing establishments	74.01	25.99	74.46	25.54
Community services	79.58	20.42	76.84	23.16
By firm size				
2-5 people staff	96.24	3.76	94.34	5.66
6-9 people staff	91.30	8.70	90.80	9.20
10-49 people staff	88.14	11.86	87.93	12.07
50-199 people staff	85.52	14.48	87.18	12.82
200 and more	78.12	21.88	77.91	22.09
By other Chilean dialect command				
Speaks and understands	94.17	5.83	95.44	4.56
Just understands	92.80	7.20	89.89	10.11
None	86.43	13.57	90.91	9.09

Source: CASEN Survey.

Table 2: Individuals characteristics

	2000		2006	
	$C = 0$	$C = 1$	$C = 0$	$C = 1$
CLP wage average per hour ($)	1,089 (1780.143)	2,109 (2327.191)	1,250 (1534.923)	2,471 (2559.041)
Average Schooling years	10.2 (4.045371)	14.0 (2.775211)	10.5 (3.777043)	14.1 (2.699682)
Average work experience	21.9 (13.54067)	16.9 (10.50214)	22.6 (14.41603)	17.2 (10.64737)
Average age	38.1 (12.0825)	36.9 (10.40505)	39.0 (12.86384)	37.2 (10.46666)

Note: Standard Deviation in parenthesis.
Source: CASEN Survey.

Table 3: Workplace computer use probability determinants

Individual characteristics			**Firm characteristics**		
	2000	**2006**		**2000**	**2006**
Variable	**dF/dX**		**Variable**	**dF/dX**	
Schooling	0.05109** (0.005928)	0.0505519* (0.007278)	Not well-specified activities	0.4714734* (0.0789159)	0.4166436* (0.0561078)
Squared Schooling	-0.0011626** (0.0002499)	-0.0009517* (0.0003063)	Mining	0.1995263* (0.0323557)	0.2222502* (0.0299894)
Age	0.0021851 (0.0014259)	0.0076933* (0.0013647)	Manufactures	0.160484* (0.0187686)	0.1908071* (0.0174376)
Squared age	-0.0000282 (0.0000183)	-0.0000963* (0.0000176)	Electricity, gas and water	0.3066099* (0.1062183)	0.2599019* (0.0536186)
Urban zone dummy	0.0552957** (0.0058731)	0.0511506* (0.0052291)	Construction	0.0653391* (0.0192049)	0.0770518* (0 .0165851)
			Commerce	0.2369385* (0.0221214)	0.2793078* (0.020127)
			Transport and communications	0.1637858* (0.0248459)	0.1737544* (0.0210403)
			Financing establishments	0.3575333* (0.0271363)	0.3708225* (0.0237217)
			Community services	0.2640189* (0.0218175)	0.3132668* (0.0189149)
			2-5 people staff	-0.0593033* (0.0106228)	-0.0491173* (0.0100024)
			6-9 people staff	0.0036084 (0.0177366)	-0.0095201 (0.0146166)
			10-49 people staff	0.044894* (0.0145744)	0.021554** (0.011445)
			50-199 people staff	0.0687304* (0.0166633)	0.0378115* (0.0122254)
			200 and more people staff	0.1160142* (0.01734)	0.1003233* (0.0121227)
N	35,994	43,519		36,427	43,627
Pseudo R^2	0.1571	0.1676		0.0942	0.0904

Notes: *z* test in parenthesis, * 5% significant, ** 10% significant.
Source: CASEN Survey.

Table 4a: Workplace computer use returns estimation (CASEN 2000)

Variable	**(1)**	**(2) = (1) + geographic region**	**(3) = (2) + firm size**	**(4) = (3) + economic sector**
Schooling	0.0487657 (0.0037828)**	0.0443433 (0.0036573)**	0.041885 (0.003487)**	0.040372 (0.0035285)**
d8(Schooling-8)	0.0446405 (0.0063058)**	0.047036 (0.0060308)**	0.0419997 (0.0057952)**	0.0403795 (0.0058068)**
d12(Schooling-12)	0.1370266 (0.0075117)**	0.1345369 (0.0071805)**	0.1355114 (0.0071116)**	0.1383247 (0.007081)**
Work experience	0.0294806 (0.0014283)**	0.0303785 (0.0013743)**	0.0285809 (0.001352)**	0.0279305 (0.0013415)**
Squared work experience	-0.0003378 (0.0000251)**	-0.0003599 (0.0000243)**	-0.0003309 (0.0000237)**	-0.0003204 (0.0000234)**
Urban zone Dummy	0.2240331 (0.0096136)**	0.1409606 (0.0100973)**	0.0988731 (0.0099649)**	0.0577598 (0.0128933)**
Computer dummy	0.2146034 (0.0232843)**	0.2158327 (0.0216616)**	0.1839566 (0.0223724)**	0.1788722 (0.0217439)**
Constant	5.253697 (0.0321)**	5.280345 (0.0380447)**	5.313291 (0.0409149)**	5.253619 (0.0404894)**
N	35,994	35,994	35,994	35,994
R^2	0.5129	0.5363	0.5548	0.5667

Notes: *t* test in parenthesis, * 5% significant, ** 1% significant, d8=1 If Schooling > 8, d12=1 If Schooling > 12.

Table 4b: Workplace computer use returns estimation (CASEN 2006)

Variable	**(1)**	**(2) = (1) + geographic region**	**(3) = (2) + firm size**	**(4) = (3) + economic sector**
Schooling	0.0403136 (0.0036045)**	0.0375074 (0.003485)**	0.0347399 (0.0033731)**	0.0330286 (0.0033851)**
d8(Schooling-8)	0.0355728 (0.0056996)**	0.0362499 (0.0055176)**	0.033674 (0 .0053549)**	0.0346698 (0.0053451)**
d12(Schooling-12)	0.1260061 (0.0057315)**	0.1253307 (0.005623)**	0.12584 (0.0055307)**	0.126518 (0.0056393)**
Work experience	0.0255668 (0.0010396)**	0.0261098 (0.0010288)**	0.0256441 (0.0010162)**	0.0250896 (0.0010138)**
Squared work experience	-0.0002903 (0.0000189)**	-0.0003045 (0.0000186)**	-0.0002981 (0.0000183)**	-0.0002878 (0.0000182)**
Urban zone Dummy	0.1420268 (0.0077592)**	0.0799269 (0.0082485)**	0.0523317 (0.0081278)**	0.0118935 (0.0089898)**
Computer dummy	0.2067873 (0.0177663)**	0.2045624 (0.0174206)**	0.1816503 (0.0172134)**	0.1814486 (0.016965)**
Constant	5.745563 (0.0280248)**	5.745569 (0.0336882)**	5.749524 (0.034139)**	5.708909 (0.0338334)**
N	43,519	43,519	43,519	43,519
R^2	0.4422	0.4604	0.4771	0.4878

Notes: *t* test in parenthesis, * 5% significant, ** 1% significant, d8=1 If Schooling > 8, d12=1 If Schooling > 12.

Table 5: Probability for matching implementation

	2000	2006
Variable	**Coefficient**	**Coefficient**
Schooling	0.1317677** (0.0003843)	0.1489743** (0.0003811)
Age	0.0121387** (0.0006545)	0.0529367** (0.0006214)
Squared age	-0.0002072** (0.0000082)	-0.0006882** (000000796)
Urban zone	0.3915546** (0 .0065296)	0.2793047** (0.0053032)

Notes: Region, firm size, and economic sector controls was included. *t* test in parenthesis, * 5% significant, ** 1% significant.
Source: CASEN Survey.

Table 6: Probability errors Normality test

	2000	2006
Variable	**Coefficient**	**Coefficient**
Schooling	0.1808254** (0.0011362)	0.1789121** (0.0011135)
Age	0.019644** (0.0006879)	0.0627208** (0.0007641)
Squared age	-0.0003035** (0.00000871)	-0.0008091** (0.00000978)
Urban zone	0.4029429** (0.0070799)	0.2898042** (0.005545)
$\hat{P}(\cdot)^2$	-0.8484842** (0.160172)	-0.8308466** (0.1219675)
$\hat{P}(\cdot)^3$	-4.798909** (0.2365525)	-1.270424** (0.1617654)
Constant	-4.758228** (0.0236297)	-5.443516** (0.0271999)
N	36,018	43,620

Notes: Region, firm size, and economic sector controls were included. *t* test in parenthesis, * 5% significant, ** 1% significant.
Source: CASEN Survey.

Table 7: Program impact (in $ CLP wage per hour)

	Impact mean (%)	
Method	**2000**	**2006**
Nearest neighbor	28.4	16.3
Three nearest neighbors	23.7	14.7
Five nearest neighbors	26.5	16.2
Kernel (h_n = 0.06)	26.2	19.6

Source: CASEN Survey.

Table 8: Impact program: sub-group (in $ CLP wage per hour) (CASEN 2006)

	Impact mean (%)	
	Probit	**Klein-Spady**
Method		
Nearest neighbor	21.3	42.9
Three nearest neighbors	18.8	45.3
Five nearest neighbors	18.6	41.7
Kernel (h_n = 0.06)	20.1	45.2

Figure 1: Skilled workers versus non-skilled workers

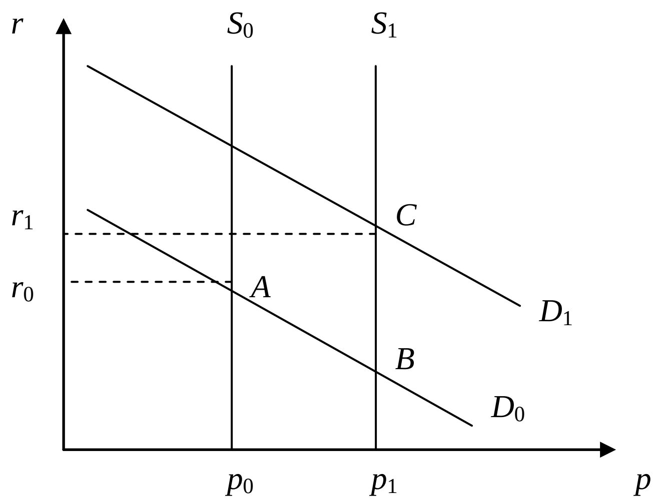
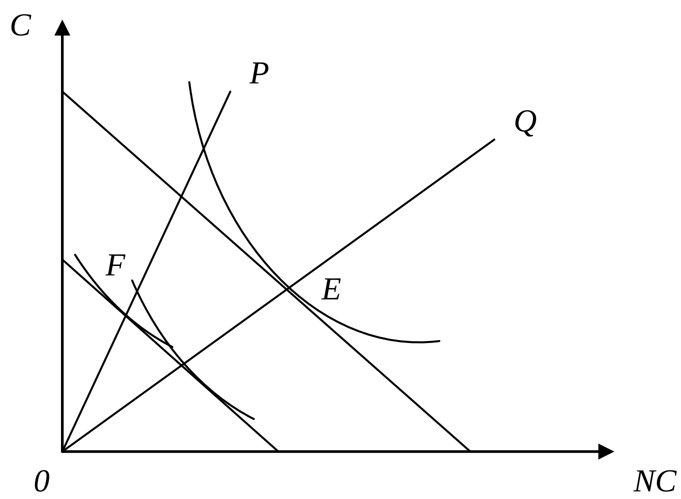


Figure 2: Technological changes by skilled workers biased



Appendix A: Technological Change, Computers and Salaries

Computers, given the aforementioned definition, are more substitutable with the labor factor in the execution of routine tasks than in non-routine tasks, as indicated in Autor *et al* (2001). [12] Secondly, the non-routine and routine tasks are in some way substitutable. Finally, the greater the intensity of factors to carry out routine tasks the greater the marginal productivity of the factors in charge of carrying out the non-routine tasks.

Specifically, consider a production function in which the routine (R) and non-routine (N) tasks are used in the production of final goods (q), which is sold for a unitary price. The following Cobb-Douglas type function will be assumed:

$$q = R^{1-\beta} N^{\beta} \qquad (1)$$

where $0<\beta<1$ and physical capital computer (C) and workers have some degree of substitutability in the execution of routine tasks, but not in the non-routine tasks. Computer capital is offered elastically for a P price per unit in the market. It is assumed that the price of computers evolves exogenously and decreasingly over time, whereby the notion of technological change is introduced.

Regarding job vacancies, the Roy model (1951) is followed, where the workers choose between occupations (routine and non-routine) according to their comparative advantages. Each worker has a productivity $E(R_i,N_i)$ in the execution of routine and non-routine tasks, specified in efficiency units, where $R_i,N_i > 0$ for all i. The relative efficiency of the individual i in the execution of non-routine tasks versus the routine tasks is defined as $\alpha_i = N_i/R_i$ where $\alpha \in (0,\infty)$.

It is assumed that there is a great number of workers that have to choose between offering R_i efficiency units in routine tasks or N_i efficiency units in non-routine tasks exist. The selection made by the worker between both types corresponds to the occupational choice of the individual.

[12] Since the substitutable elasticity between routine and non-routine tasks for a Cobb-Douglas type production function is one, the physical capital and the non-routine tasks are complementary in certain ways.

Subsequently, the consequences of a technological change over occupational choice, marginal productivity in routine and non-routine tasks and wages (specified in efficiency units) must be established. The technological change in this model will be represented by a fall in the price of computers, which will in turn lead to its greater penetration in productive activities in general.

If the computer and the workers with skills in routine tasks are perfect substitutes, the salary for efficiency unit for routine tasks will be:

$$W_R = P \tag{2}$$

Meanwhile, if the worker has to choose his/her occupation in order to maximize his/her incomes, the marginal worker with α^* relative efficiency units in non-routine versus routine tasks will be indifferent between a routine and non-routine occupation while:

$$\alpha^* = \frac{W_R}{W_N} \tag{3}$$

Therefore, in the case of $\alpha_i < \alpha^*$, individual *i* offers work in the routine sector, and for $\alpha_i \geq \alpha^*$, individual *i* offers work in the non-routine sector.[13]

The labor force in efficiency units dedicated to routine and non-routine tasks will be $g(\alpha)$ and $h(\alpha)$, respectively, for each value of α. An optimum behavior requires that the factors should be paid in accordance with their marginal contribution to the production process. Therefore, arising from (1) we have that:

---

[13] The aforementioned condition is equivalent to:

$$NW_N < RW_R$$

In other words, the value of the marginal productivity in the routine sector is greater than the one in the non-routine sector.

$$W_R = \frac{\partial q}{\partial R} = (1-\beta)\theta^{-\beta} \tag{4}$$

$$W_N = \frac{\partial q}{\partial N} = \beta\theta^{(1-\beta)} \tag{5}$$

Where:

$$\theta = \frac{C^* + \int_0^{\alpha^*} g(x)dx}{\int_{\alpha^*}^{\infty} h(x)dx} \tag{6}$$

So, θ is the ratio between routine and non-routine tasks in the production. Meanwhile, C^* is the quantity of computers used in equilibrium, and it is determined as a remainder once the individuals have chosen how much routine work they will offer in the market.

The θ variable is endogenous, and it is crucial in this model. The factors that increase the relative intensity of the routine tasks (θ) reduce the wage per efficiency unit of the routine task factors. The opposite occurs with wage from the non-routine task factors. Arising from (2) and (4) we have:

$$W_R = P = (1-\beta)\theta^{-\beta} \tag{7}$$

Thus, solving for θ we have that:

$$\theta = \left(\frac{1-\beta}{P}\right)^{\frac{1}{\beta}} \tag{8}$$

Therefore, when P diminishes the intensity of the routine tasks increases (since it has a lower cost). Meanwhile, if we apply logarithms to (7), we have that:

$$\ln(W_R) = \ln(P) = \ln(1-\beta) - \beta\ln(\theta)$$

And differentiating with respect to ln(P) the following expression is obtained:

$$\frac{\partial \ln(W_R)}{\partial \ln(P)} = 1 = -\beta \frac{\partial \ln(\theta)}{\partial \ln(P)}$$

Or:

$$\frac{\partial \ln(\theta)}{\partial \ln(P)} = -\frac{1}{\beta} \tag{9}$$

Therefore, a reduction in the price of computers reduces the wage per efficiency unit of routine tasks and increases the relative intensity of the routine tasks in the productive process.

Meanwhile, if we apply logarithms to (5), we have that:

$$\ln(W_N) = \ln(\beta) + (1-\beta)\ln(\theta)$$

And differentiating with respect to ln(*P*):

$$\frac{\partial \ln(W_N)}{\partial \ln(P)} = (1-\beta)\frac{\partial \ln(\theta)}{\partial \ln(P)}$$

Finally, replacing with (9) the following expression is obtained:

$$\frac{\partial \ln(W_N)}{\partial \ln(P)} = \frac{\beta - 1}{\beta} \tag{10}$$

So, a reduction in the price of the computer increases the marginal productivity of the workers assigned to non-routine tasks, which is related to complementarities between routine and non-routine tasks. Therefore, when price of computers diminishes, their penetration in the various economic activities increases. Then, these computers begin to be assigned to those individuals that are more productive with them in the companies, in other words, with more skills associated to their use.

Since wages are expressed in terms of efficiency units, and since efficiency units vary between the population and that workers choose their occupations to maximize their incomes, then a reduction in the price *P* of the computer changes the occupational choice of the individual.

For example, consider the impact that a fall in the price of computers has on the relative efficiency of the marginal worker in the routine occupation. If we apply logarithms to (3), we have that:

$$\ln(\alpha^*) = \ln(W_R) - \ln(W_N)$$

Differentiating with respect to ln(*P*):

$$\frac{\partial \ln(\alpha^*)}{\partial \ln(P)} = \frac{\partial \ln(W_R)}{\partial \ln(P)} - \frac{\partial \ln(W_N)}{\partial \ln(P)} = 1 - \left(\frac{\beta - 1}{\beta}\right)$$

Therefore:

$$\frac{\partial \ln(\alpha^*)}{\partial \ln(P)} = \frac{1}{\beta} \qquad (11)$$

In this way, a fall in the price of computers diminishes the employment supply in the routine occupations and increases the employment supply in the non-routine occupations. The aforementioned occurs because a fall in the price of computers depresses the wages in the routine sector which, at the same time reduces the employment supply in that sector. When employment offer increases in the non-routine occupations, less skilled individuals, in relative terms, will start to enter, then the average skills of people who use a computer in the labor market diminishes. The aforementioned should determine a fall in the premium associated to the use of computers at the workplace (Krueger 1993).

Meanwhile, as indicated above, the fall in the price of computers increases the relative intensity of the routine tasks factor. However, there is also a contraction in the offer of the factor dedicated to those activities. Then, to achieve the increase in intensity of the use of that factor, an increase in the demand that compensates at least the fall in the employment supply is needed:

$$\frac{\partial \ln(C^{*})}{\partial \ln(P)} < -\frac{\partial \int_{0}^{\alpha^{*}} g(x)dx}{\partial \ln(\alpha^{*})} \frac{\partial \ln(\alpha^{*})}{\partial \ln(P)} < 0 \tag{12}$$

In other words, although a fall in the price of computers contracts the employment supply destined to routine tasks $\int_{0}^{\alpha^{*}} g(x)dx$, the increase in the quantity of equilibrium computers (*C**) compensates the contraction.

In summary the model establishes two important facts: (i) there is a return for using a computer at work, and (ii) this premium should be decreasing with computers penetration.

Appendix B: Klein and Spady semi-parametric estimator

A non-parametric estimate could be carried out; however, since Z_i' is multidimensional, there is the problem of the dimensionality curse. This is why a semi-parametric estimate will be carried out:

Let:

$$Z_i'\gamma = \gamma_1 + \gamma_2 Z_{2i} + \cdots + \gamma_q Z_{qi}$$

Then:

$$Z_i'\gamma = \gamma_1 + \gamma_2(Z_{2i} + Z_{3i}\theta_1 + \cdots + Z_{qi}\theta_{q-2})$$

Therefore:

$$Z_i'\gamma = \gamma_1 + \gamma_2 v(Z_i, \theta)$$

where:

$$v(Z_i, \theta) = Z_{2i} + Z_{3i}\theta_1 + \cdots + Z_{qi}\theta_{q-2}$$

with:

$$\theta_j = \frac{\gamma_{j+2}}{\gamma_2}$$

with *j*=1,2,…, q-2, and where the parameter θ is identifiable. The key factor in the analysis is to correctly identify a continuous variable with a non-zero coefficient.[14] The function $v(Z_i, \theta)$ is termed the index and does not necessarily need to be linear.[15] The fundamental aspect is that the functional form among the parameters be known and that one of these parameters can be normalized to one.

[14] That is $\gamma_2 \neq 0$. The school variable will be considered here.
[15] There are two assumptions: constant equal to zero and γ_2 equal to one.

We determined that $v(Z_i, \theta)$ would have a non-zero coefficient in some continuous variable; therefore this function has a continuous distribution. To simplify the notation, it is termed $f(v)$. It is defined as:

$$P(C=1 \mid X) = P(C=1 \mid v) = \frac{f(C=1 \mid v)}{f(v)}$$

$$P(C=1 \mid X) = \frac{f(v \mid C=1)P(C=1)}{f(v \mid C=1)P(C=1) + f(v \mid C=0)P(C=0)}$$

The conditional densities are estimated non-parametrically in the following manner:

$$f(v|C=1) = \frac{1}{NP(C=1)h_N}\sum_{i=1}^{N} C_i K\left(\frac{v - Z_i'\gamma}{h_i}\right)$$

and:

$$f(v|C=0) = \frac{1}{N(1-P(C=1))h_N}\sum_{i=1}^{N} (1-C_i) K\left(\frac{v - Z_i'\gamma}{h_i}\right)$$

The unconditional probabilities are estimated by means of sample averages. $\hat{P}(C=1 \mid v)$ it is defined as the estimator obtained, and the quasi-function of verisimilitude as:

$$\log(L) = \sum_{i=1}^{N} (1-C_i)\log[1-\hat{P}(C=1 \mid v)] + C_i \log[\hat{P}(C=1 \mid v)]$$

Differentiating with respect to θ, it holds that:

$$\frac{\partial \log(L)}{\partial \theta} = \sum_{i=1}^{N}\left(\frac{\partial \hat{P}(C=1 \mid v_i)}{\partial \theta}\right)\hat{P}(C=1 \mid v_i)^{-1}[1-\hat{P}(C=1 \mid v_i)]^{-1}[C_i - \hat{P}(C=1 \mid v_i)] = 0$$

The Klein and Spady semi-parametric estimator is obtained by maximizing this expression.