CHILEAN LABOR MARKET EFFICIENCY: AN EARNINGS FRONTIER APPROACH*

SERGIO SALAS LANDEAU
DANTE CONTRERAS

Abstract

In this paper, we use the econometric frontier approach to estimate efficiency measures of the transformation of human capital into earned income in the Chilean labor market for the period 1957-1998. We find that the mean efficiency is 75%, and that it has been improving over time. We also find evidence of detrimental effects of non market oriented governments on these efficiency measures. Some evidence is also found about the effects of health on efficiency, the existence of labor market segmentation and the importance of "social networks". Finally we calculate correlation measures and casuality tests between the estimated efficiencies and the rate of growth of GDP, finding a statistical precedence of the former to the later. We give then an appealing explanation for this result.

Resumen

Este trabajo utiliza el enfoque de fronteras de eficiencia para estimar medidas de eficiencia de la transformación de capital humano en ingreso para el mercado laboral chileno entre 1957 y 1998. Encontramos que la eficiencia fue aumentando con el tiempo y que su media es del 75%. También se encuentra evidencia del efecto negativo que tuvieron los gobiernos no orientados al mercado en la medida de eficiencia. También se encuentra alguna evidencia del efecto de la salud en la eficiencia, la existencia de mercados segmentados y la importancia de "redes sociales". Finalmente, se encuentra que el crecimiento del PIB precede estadísticamente a las medidas de eficiencia y proveemos una explicación para que esto ocurra.

Keywords: *Efficiency, Labor, Frontier approach, Chilean labor market.*

JEL Classification: *I120, JO.*

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□ Department of Economics of the University of Chile. E-Mails: ssalas@econ.uchile.cl and dcontrer@econ.uchile.cl

1. Introduction

One of the most active areas in labor economics has been the human capital theory and the estimation of the earnings equation, which was first postulated by Mincer (1974).

Most of the work in previous studies on the subject was focused on the problems raised from the omission of relevant variables (many of them even unobservable). Some of the mechanisms devised to overcome this problem are the use of instrumental variables or the fixed effects panel estimation (whenever it is possible). One study for Chile along these lines is Contreras, Bravo and Medrano (1999), where they incorporate in the earnings equation additional variables traditionally not available (like a good proxy for individual's skills). Evidence for international studies can be found (to mention a few) in: Angrist and Krueger (1991), Card (1993), Ashenfelter and Krueger (1994), Ashenfelter and Zimmerman (1995) and Lam and Schoeni (1993).

Even though a lot of effort has been done in estimating properly the earnings equation, these studies have not been faithful to the theoretical concept of a production function, which underlies the concept of human capital and the earnings equation. In a sense, the mentioned studies have been estimating "average" earnings rather than potential earnings.

The concept of potential earnings raise naturally for the estimation of the earnings equation since its basis is the human capital theory, which in turn borrows heavily from the neoclassical theories of investment and production. Investment in human capital in the form of schooling, work experience, etc., represents the inefficiency in the transformation of human capital into earned income. Several interesting questions can be addressed with these estimations such as measuring the degree of informational inefficiency of the employees, the degree of market power of employer, segmentation and discrimination.[1]

2. The Model and Estimation Techniques

Two different forms of estimating potential earnings have been devised. One is the deterministic frontier and the other is the stochastic frontier.

The deterministic frontier proposed by Greene (1980), assumes that each deviation from this frontier is due to inefficiency. This feature accords with the theoretical concept of a frontier as an upper bound for the actual values of the dependent variable. As a practical framework for modelling the observed values of labor market earnings however, this approach is rather restrictive and perhaps misleading since it may confound earnings inefficiency with the effects of underspecification and measurement errors, usually considered important in the estimation of an earnings equation. Moreover, under the deterministic frontier estimation, an unusually high number of the dependent variable (or an outlier problem), might ultimately appear to the analyst as inefficiency.

1 Some studies that used this methodology to address these questions are: Lang (2000), Robinson and Wunnava (1989) and Croppenstedt and Meschi (1998).

The stochastic frontier proposed by Aigner, Lovell and Schmidt (1977) consider the fact that the frontier itself might be stochastic. In particular, as explained in more detail below, the stochastic frontier is modelled with a composite disturbance in the earnings equation. One component of this disturbance is assumed to be normally distributed with zero mean and represents specification and measurement error, and the other component is assumed to be a random variable with non positive distribution.

We now proceed to briefly discuss the main features of the stochastic frontier estimation since it is the one used in this study.

Stochastic Frontier

Aigner, Lovell and Schmidt (1977) proposed a composite disturbance structure for the frontier model in which one normally distributed component represents specification and measurement errors and the other, half normally distributed disturbance term captures inefficiency. The stochastic earnings frontier may be written as:

$$(1) \qquad LnE_i = \alpha + \beta X_i + v_i - \mu_i \qquad \text{i = 1,2,…N}$$

where E_i is observable earning for the i_{th} individual, X_i is a vector of explanatory variables, white noise is represented by: $v_i \sim N\left(0, \sigma_v^2\right)$, whereas μ_i reflects labor market inefficiency of a specific person i. The stochastic term μ_i is restricted to be non-negative because otherwise one would be allowed to earn more than the potential (maximum) earnings which is given by: $\alpha + \beta X_i + v_i$. Then, with this specification, consequences of measurement error and specification problems are expected to be taken into account with the normally distributed variable v_i. To estimate the parameters of the underlying function, the stochastic distribution of the inefficiency term μ_i has to be specified. The most popular assumption is the half normal distribution, introduced by Aigner *et al.* (1977). The log likelihood function for the associated distributions is:

$$(2) \quad LnL = \sum_{i=1}^{n}\left[-Ln\sigma + Ln\frac{\sqrt{2}}{\sqrt{\pi}} - \frac{1}{2}\frac{\left(LnE_i - \alpha - \beta X_i\right)^2}{\sigma^2} + Ln\Phi\left(\frac{-\left(LnE_i - \alpha - \beta X_i\right)\lambda}{\sigma}\right)\right]$$

where $\Phi(\cdot)$ is the standard normal distribution function, and $\sigma^2 = \sigma_v^2 + \sigma_\mu^2$, $\lambda = \sigma_\mu / \sigma_v$.

With estimates from (2) an estimator of the compound residual $\varepsilon_i = v_i - \mu_i$ is feasible. Following Jondrow *et al*. (1982) and Greene (1993), the indirect way to recover μ_i is using the conditional expectation of μ_i given ε_i:

$$(3) \qquad E\left[e^{-\mu_i} \middle| \varepsilon_i\right] = \frac{\Phi\left[\mu_i^* / \sigma_* - \sigma_*\right]}{\Phi\left[\mu_i^* / \sigma_*\right]}$$

where $\mu_i^* = (1-\gamma)(-\varepsilon_i), \sigma_*^2 = \gamma\sigma_\mu^2, and \ \gamma = 1/\left(1+\lambda^2\right)$.

Of course one must obtain an estimate of these mean and since μ is restricted to be non-negative, this estimate would be between 0 and 1, this number gives the proportional efficiency recalling that the inefficiency was assumed implicitly to be multiplicative (see equation 1). Then:

$$EFF_i = \frac{e^{(\alpha+\beta X_i + v_i - \mu_i)}}{e^{(\alpha+\beta X_i + v_i)}} = e^{(-\mu_i)} \tag{4}$$

The upper bound of this measure represents a worker who transforms his human capital endowment perfectly into market income.

3. Data Description

The data available for this study corresponds to the Employment and Unemployment survey of the Metropolitan Region of the University of Chile for almost the entire period: 1957-1998.[2] The survey contains useful information on age, gender, occupational status, working hours, monthly income and level of schooling. Also in the last year available, new important variables are included such as actual experience, education of the mother and father, education of the mother and father in law, religion, weight, height and whether the surveyed uses computer at work.

For this study we limit our database to include only blue collar and white collar workers with more than 30 working hours per week. We also omit females to avoid the selection bias problem, then our results would only be valid for male workers.

Table 1 shows a brief statistical description of the variables in the 1998 database.

4. Empirical Results

The behavior of efficiency over time

In this subsection an estimation is made for the average efficiency for each year of the available database.

We define for each year the same stochastic frontier, in which the vector X, includes only four variables (proxies of human capital), schooling (sch), squared schooling (sch^2), experience (expe) and squared experience (expe^2). The inclusion of these variables are directly justified by the human capital theory. There is a large literature concerned with the effects of the omission of relevant variables in the parameters of the model, we tackle then this concern with regard the estimation of the efficiency measure, and we show later that there is not a significant change in this estimate when we include additional variables traditionally considered omitted.

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[2] Three years data are missing: 1959, 1963 and 1964.

TABLE 1
DATA DESCRIPTION

Variable*	Mean	Definition
LnE	2.25	Natural logarithm of monthly income divided by monthly working hours
sch	11.1	Number of grades in school and university completed
expe	6.98	Actual working experience
sch_fa	7.92	Number of grades in school of the father
sch_mo	7.44	Number of grades in school of the mother
bmi	0.25	Biomass index = kg/(m)^2
compu	0.32	Equals 1 if use computer at work 0 otherwise
d_pub	0.076	Equals 1 if working in public sector 0 otherwise
agric	0.01	Equals 1 if working in agricultural sector 0 otherwise
min	0.006	Equals 1 if working in mining sector 0 otherwise
ind	0.26	Equals 1 if working in industrial sector 0 otherwise
const	0.17	Equals 1 if working in construction sector 0 otherwise
com	0.16	Equals 1 if working in commerce sector 0 otherwise
sefin	0.14	Equals 1 if working in financial services sector 0 otherwise
seper	0.04	Equals 1 if working in personal services sector 0 otherwise
secom	0.09	Equals 1 if working in communal services sector 0 otherwise
trans	0.11	Equals 1 if working in transport sector 0 otherwise
sch_mol	5.25	Number of grades in school of the mother in law
sch_fal	5.5	Number of grades in school of the mother in law
ca_r	0.73	Equals 1 if catholic 0 otherwise

* 1466 observations.

We estimate the equation (1) for every year by maximum likelihood using the log likelihood expressed in (2). With this estimation we are able to recover the mean efficiency measure expressed in equation (4) for each individual, the point estimate result then averaging this mean efficiencies over the n individuals in each year. Moreover, confidence intervals for this estimate were computed for each year to verify if there are significative differences across years in these estimates. These confidence intervals were calculated using the equation (3), in principle a confidence interval could be calculated for each individual every year, instead of that, we use the average over individuals of the measure (3) and use the asymptotic properties (Slutsky, Mann Wald, etc.) to compute confidence intervals for this average each year. The results can be seen in Figure 1 (see appendix).

By visual inspection of Figure 1, one can assert that there is no clear tendency in the overall series. Nonetheless, it turns out that the best curve that fit the series is a convex function (not reported here).

The confidence intervals (calculated at 95% confidence) indicate that in general the estimates are acceptable considering that the percentage efficiency estimate is by construction between 0 and 1, most of the estimates before 1989 are precise estimates with very small confidence intervals. This changes somewhat in the nineties.

The overall mean efficiency is about 75%. For the seventies the mean is 72%, for the eighties the mean is 73% and 80% for the nineties, this would suggest that the efficiency measure has been improving over time. For purposes of comparison, we know that this measure is 86% for the USA (Hunt-McCool and Warren (1993)) and 75-80% for Germany (Lang (2000)).

One point in the series that is worth to highlight is the deep fall in the efficiency measure in the years 1971 to 1973. Since this is a period where the government was heavily characterized by a state ownership economy in Chile (former President Allende), this would suggest that schemes of government far away from market orientation have undesirable consequences for labor efficiency. The channels by which this effect may come from are two. First the notion of returns to human capital is not clear or may not apply in a socialist economy, because the role of competitive equilibrium which leads to pay marginal productivity is reduced. Second the role of information in prices (which is central in a market based economy) is somehow absent in a state ownership economy. Then, the labor factor could have had a less degree of transformation of human capital into earned income because informational inefficiencies: workers did not have enough information to seek for jobs that pay in accordance with their human capital accumulation.

It is also interesting to mention that there are some points in the efficiency series that seems to follow the same pattern of the rate of growth of GDP, for example, the pattern of falls in periods 1975 and 1982 corresponds to periods of recession in Chilean economy (see figure 2 for a comparison between the efficiencies and the rate of growth of GDP). Furthermore, it is interesting to mention that the deepest recession of Chile (1982) have a milder impact on efficiency than the political regime of Allende. This suggest the deep harm of the lack of competition or political environment in the efficiency measure. Also, there seems to be some correlation in other periods between the rate of growth of GDP and the efficiency measure.[3] We return later to explore further and more formally the possibility of a statistical significative relationship between this two series and its economic implications.

Once this general picture about the behavior of efficiency over time has been shown and before going on with further analysis, it is convenient to check if these measures change as a result of the inclusion of new variables. This is accomplished in the next section considering the last database available: 1998, which incorporates new variables.

The effect of omitted variables

The variables included in the 1998 database are described in table 1. Our approach to check if the efficiencies measures are sensitive to the omission of relevant variables is an empirical one. In addition to the variables considered in

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3 It would be a mistake to relate these correlations to changes in the value of marginal product of labor in the cycle, because these changes are already incorporated in the estimation of the frontier.

the calculations of efficiencies in figure 1 (schooling and its squared, experience and its squared) we now incorporate new variables: we estimate equation (1) with the following *X* vector: schooling (sch), squared schooling (sch^2), experience (expe), squared experience ($expe^2$), schooling of the father (sch_fa), schooling of the mother (sch_mo) and a dummy for the use of computer at work (compu). The result are shown in Table 2.

The reason to include schooling of father and mother is to take into account for the skills of the person (see Lam and Schoeni (1993) and Ashenfelter and Krueger (1994)). The dummy compu is included because it is expected that productivity raises with the use of computer.[4] The important result is that the average efficiency measure is virtually unchanged. Then on overage a worker can transform 82% of his human capital into income (18% of inefficiency). In a similar result found for USA, Hunt-McCool and Warren (1993) found an aver-

TABLE 2
ESTIMATION FOR 1998

Variable	ML Stochastic
Constant*	1.1639
	(0.0866)
Schooling (sch)*	–0.0713
	(0.0135)
Schooling squared (sch^2)*	0.0073
	(0.0007)
Experience (expe)*	0.037
	(0.0045)
Experience squared ($expe^2$)*	–0.0007
	(0.0001)
Schooling of the father (sch_fa)*	0.0144
	(0.0054)
Schooling of the mother (sch_mo)	0.0075
	(0.0055)
Use of computer (compu)*	0.2920
	(0.0354)
σ^{2*}	0.4680
	(0.043)
λ^*	–1.3409
	(0.1814)
Mean Log Likelihood	–0.770577
Number of individuals	1465
Year	1998
Average Efficiency	0.82

* 5% significative, asymptotic standard errors in parenthesis.

[4] For a discusión about the importance of this variable see Katz and Krueger (1998) and Krueger (1993).

age inefficiency of 14%. Additionally the corresponding return to schooling for this year evaluated at the mean of the schooling variable, gives an estimate of 9% which is statistically different from zero according to a test of the restriction: –0.0713 + 2 x 0.0073 x $\overline{sch}$, where $\overline{sch}$ is the average of schooling (with a value for this test of 19,64 distributing X^2 with one degree of freedom). This finding is consistent with other estimations of returns to schooling for the Chilean case (see for example Contreras *et al*. (1999)).

There are several important statistical results about the relative importance of assuming two different distributions for the error terms v and μ respectively, in comparison with the traditional practice of estimating a Mincer equation by OLS. In this case it is assumed that inefficiency is nonexistent, so if this is indeed the case, we should find that the mean of the efficiency component of the innovation is zero: E(μ) = 0. Computing a test for this hypothesis led us to a t-statistic of 7.93, implying a rejection of the OLS estimator. Similarly the measure λ in equation (2) is useful because in the case of being zero, this would imply that there is no stochastic inefficiency (because this implies $\sigma^2_\mu = 0$), again a t-statistic for this hypothesis (3.97) indicates the good relative specification of the compound residual model rather than the OLS estimate.[5]

Another useful measure we want to examine is the contribution of the inefficiency variance to total variance in explaining income differentials. The variance decomposition (the contribution of the variance of μ to the total variance is $\left[(\pi/2)-1\right]\sigma^2_\mu / \sigma^2_v + \left[(\pi/2)-1\right]\sigma^2_\mu$) led us to conclude that 51% of the estimated variance of the composite error is assigned to earnings inefficiency and the remaining part represents unexplained variability. This would suggest that half of the unexplained variability in income usually attributed to heterogeneity and underspecification may be due to inefficiency differences among individuals.[6]

In an attempt to overcome the bias problems of relevant omitted variables, many studies have incorporated many more variables in the Mincer equation, than we have had (for example Contreras *et al*. (1999)). Since our purpose is to check if there are some bias in the efficiency estimate because of the omission of relevant variables, we now proceed to estimate equation (1) under a much more wider vector X, which now includes in addition to the ones taken in the last estimation: the biomass index and its squared (bmi and bmi^2), a dummy for working in the public sector (d_pub), a series of dummies for working in different sectors of the economy; industry, agricultural, mining, construction, commerce, financial services, personal services, communal services and trasport (C, agric, min, const, com, sefin, seper, secom, trans), also the schooling of mother in law (sch_mol), schooling of father in law (sch_fal) and a dummy indicating whether the worker is catholic or not (ca_r). Each of this variables can be justified as having an effect in the income that workers perceive: For example for the biomass index (and its squared for allowing to diminishing

5 Greene (1990) point out that since under the null this tests are at the boundary of the parameter space, one should be cautious in the interpretation of the test.

6 This is an interesting result, but it is not clear what are the causes of these different inefficiencies we have encountered. Moreover it is not clear also what determine this inefficiencies. In the following sections we have something more to say about these question.

returns), Strauss and Thomas (1998) argue extensively about the influence of several health variables in improving the level of productivity. The biomass index is related to energy intake; it has also been shown to be related to maximum oxygen uptake during physical work, clearly the importance of taking into account this variable is bigger when analysing the labor market of a developing country as in this case. The inclusion of the sectoral dummies is justified again because of previous studies: Basch and Paredes (1996) with a different methodology find evidence of market segmentation in Chile.[7] Given the importance for the Chilean case of the possibility of the existence of segmented labor markets we allow for several dummies for the different sectors where the worker belongs. For the schooling of mother and father in law as well as religion it is natural to expect "social network" effects and cultural beliefs to have an effect on productivity, for a deeper discussion see Contreras *et al*. (1999).

The results of the estimation can be seen in Table 3. The important result is that once again the efficiency measure change very little, now it is close to 83%.

The results in this section suggests that the efficiencies calculated for the entire period 1957-1998, would suffer very little bias because of the omission of relevant variables.

Can we explain the inefficiencies?

So far, nothing has been said about what determines the inefficiencies we have calculated. According to the literature, there are some possible explanations about where they may come from. Three general explanations have been given, first the possibility of discrimination, which could be reflected precisely in the inefficiency measure μ, because, by definition it is the difference between a potential (Stochastic) frontier and actual earnings. Also informational inefficiencies have been considered relevant explaining this gap, this means that for some reasons, workers seeking jobs do not have enough or accurate information about the prevailing wages for different levels of human capital. Finally, a possible candidate is the market power of employer, if there is not enough competition in the labor market, employers could have monopsonic power which results in workers earning a less amount of wages than would correspond to their human capital accumulation. A similar variable that could lead to the same result as this last one, is the negotiation power of the worker, if somehow it is diminished, this could imply a level of salary under the level implied by the human capital accumulation. Of course some other possible explanations for the gap could arise and many of them will depend on the specific labor market, country or region under analysis.

One commonly used method to statistically explain estimated inefficiencies is to regress them (or their percentage complements, efficiencies) against variables considered important explaining inefficiencies. Nevertheless, for some variables, there is no consensus whether they should be part of the frontier itself or explain the gap between it and the actual earnings. This is the case for example with the variable marital status. Hunt-McCool and Warren (1993) con-

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7 They estimated a switching model to uncover the existence of a primary and a secondary labor market regimes.

TABLE 3
ESTIMATION FOR 1998

Variable	ML Stochastic	Variable	ML Stochastic
Constant	0.1799 (0.5676)	Mining (min)	–0.0019 (0.1968)
Schooling (sch)*	–0.0667 (0.0137)	Construction (const)*	0.1416 (0.0405)
Schooling squared (sch^2)*	0.0071 (0.0007)	Commerce (com)	–0.0464 (0.0389)
Experience (expe)*	0.0317 (0.0045)	Financial services (sefin)*	0.1020 (0.0475)
Experience squared ($expe^2$)*	–0.0005 (0.0001)	Personal services (seper)*	–0.2012 (0.0755)
Schooling of the father (sch_fa)*	0.0199 (0.0055)	Communal services (secom)	0.0260 (0.0562)
Schooling of the mother (sch_mo)	0.0062 (0.0054)	Transport (trans)	0.0044 (0.0480)
Biomass index (bmi)	6.312 (4.2598)	Schooling of the mother in law (sch_mol)*	0.0151 (0.0061)
Biomass index squared (bmi^2)	–10.5529 (7.975)	Schooling of the mother in law (sch_fal)	0.0063 (0.0059)
Use of computer (compu)*	0.2899 (0.0351)	Catholic (ca_r)	0.0042 (0.0294)
Public sector (d_pub)*	–01469 (0.0542)	σ^{2*}	0.4443 (0.0397)
Agricultural (agric)	–0.1359 (0.1537)	λ^*	–1.3650 (0.1722)
Mean Log Likelihood	–0.739878		
Number of individuals	1465		
Year	1998		
Average Efficiency	0.83		

* 5% significative, asymptotic standard errors in parenthesis.

sidered this variable as a component of the vector *X* (therefore being part of the frontier). Lang (2000), considered it as a factor influencing the mobility of the worker and then determining its ability to reach the potential earning. Our purpose is not to solve this discrepancies, so we proceed to follow this approach and use the calculated efficiencies from the estimation presented in Table 2, using as possible explaining variables the rest of them available in the database.[8]

We estimate by OLS a regression of the estimated efficiencies against a proxy for state of health, the biomass index and its squared (bmi and bmi^2), a dummy for working in the public sector (d_pub), a series of dummies for working in different sectors of the economy: Industry, agricultural, mining, construction, commerce, financial services, personal services, communal services

8 It is only possible to follow this approach for the year 1998, taking advantage of the new variables included in this survey.

and transport (C, agric, min, const, com, sefin, seper, secom, trans). Also additional variables have been included, the schooling of the mother in Law (sch_mol), schooling of father in law (sch_fal) and a dummy indicating whether the worker is catholic or not (ca_r).

The reason to include the biomass index is to take into account for the state of health of the individual. We use a dummy for public-private sector, considering that human capital should not systematically vary between the two sectors but assuming that other factors explain such differences as for example public workers not being paid according to their productivity. Also dummies for economic sector are taken into account, for the same reasons as to include the dummy for public sector in this stage, and also because we considered that this is an indirect way to check if there is labor market segmentation. Schooling of the mother and father in law are also introduced on the grounds that there can be social factors other than human capital that not affect productivity but the ability to get better earnings. Finally religion is also introduced to check if there are some cultural factors that affect the efficiency. Results are presented in Table 4.

This table shows that the biomass index is important to reach the frontier, working in the public sector lowers the possibility of reaching the maximum potential earnings frontier. Working in the industry (the constant in Table 4), financial services and construction sectors of the economy raises the possibility of reaching the frontier. The schooling of the mother in law also help to reach the frontier, although the effect is small. This would suggests that social factors are important. Finally, there is no significative effect of religion in the efficiency level.

In spite of the low R squared reported in Table 3, we were able to find some significative variables that explain inefficiencies. We must say however, that most of the variation of inefficiencies are unexplained with our variables.

Given our limited results in trying to explain the efficiencies with the variables at hand, we proceed to discuss the possibilities given at the beginning of this section, discrimination, informational inefficiencies and employer market power or worker power negotiation.

Discrimination is more expected to arise in two forms gender and race discrimination. Since we have omitted women for the calculations this variable is not of our concern, in relationship to race discrimination, the features of the labor market for Chile, makes us believe that this is not an important variable to worry about.

Unfortunately informational inefficiencies are hard to measure. Even though, we cannot a priori rule out the importance of this possibility, informational inefficiencies have been proved to be important specially in labor markets where immigrants are an important portion of the labor force, because this would represent a “natural barrier” for not to reach potential earnings (because of language factors, social relationships, etc.). We think that this is not the case for Chilean labor market.

Finally we end with the possible explanation of market power of employer or negotiation power of worker, we believe that this could be an important variable for Chilean labor market.

Given our results about the possible relationship between the rate of growth of GDP and the efficiency measure, in the next section we explore further this issue and link the results to this last explanation of the existence of inefficiencies.

TABLE 4
EXPLAINING EFFICIENCIES

Variable	OLS
Constant*	0.695631 (0.066855)
Biomass index (bmi)	0.851145 (0.512)
Biomass index squared (bmi^2)*	–1.43 (0.9707)
Public sector (d_pub)*	–0.0188 (0.0066)
Agricultural (agric)	–0.0188 (0.016)
Mining (Min)	–0.003381 (0.0211)
Construction (const)*	0.01539 (0.005)
Commerce (com)	–0.0051 (0.00517)
Financial services (sefin)**	0.0091 (0.0056)
Personal services (seper)*	–0.0276 (0.0086)
Communal services (secom)	–0.0054 (0.0065)
Transport (trans)	–0.0012 (0.0058)
Schooling of the mother in law (sch_mol)*	0.0017 (0.00072)
Schooling of the father in law (sch_fal)	0.0002 (0.00069)
Catholic (ca_r)	0.00038 (0.00368)
R squared	0.054
Number of individuals	1465
Year	1998
Dependent variable	Average Efficiency

* 5% significative, ** 10% significative, standard errors in parenthesis.

The role of GDP fluctuations

The discussion at the beginning of this section about the co-movements of the rate of growth of GDP and efficiencies, suggest us to make some more formal tests. To begin with, we calculate correlations between both series in different periods of time, to see if some series could lead or lag the other. Table 5 shows the results along with the calculated confidence intervals (C.I.).

We can conclude that the rate of growth of GDP does not lead the efficiency, none of the correlations in this sense is significative different from zero (with the possible exception of the correlation between the rate of growth of GDP in t and the efficiency measure in t+4), on the contrary there is evidence that the efficiency leads the rate of growth of GDP in t, because the efficiency measures in t-2 and t-3 are significative. Also the contemporaneous correlation is high, but notice that the correlation in t-2 is almost the same as in t and even grater in t-3. Also, all of the correlations calculated imply a positive relationship between the two series.

To asses further the possible statistical precedence between the series, we proceed to perform a Granger causality test between them. Estimating a VAR of order 3 (which turned out to be the optimal lag based on a likelihood ratio tests and white noise of the VAR residuals), we calculate the causality test presented in Table 6.

Given the information on Table 6 we reach the following conclusion: there is a statistical precedence of the efficiency measure to the rate of growth of GDP at 10% confidence level. The fact that this causality does not necessarily mean economic causality plus the purported employer market power argument outlined in this section, leads us to give the following possible explanation of this causality: With rational forward looking agents and an imperfect labor market where negotiations of salaries take place, an expected decrease in the rate of growth of GDP weakens the negotiation power of the worker who is forced to accept a lower salary than its human capital accumulation would enable him to earn. Then, there would be an economic causality of rate of growth of GDP to the efficiency measure, but a statistical precedence of efficiency to the rate of

TABLE 5
CORRELATIONS

	γPIB								
Efficiency	t–4	t–3	t–2	t–1	t	t+1	t+2	t+3	t+4
Corr C.I.*	0.08 [–0.22,0.38]	0.48 [0.19,0.79]	0.37 [0.11,0.7]	0.16 [–0.35,0.53]	0.40 [0.17,0.74]	0.17 [–0.2,0.4]	0.22 [–0.05,0.56]	0.07 [0.23,0.38]	0.25 [0.01,0.46]

* The confidence intervals at 5% were calculated by bootstrap using Hall's intervals with 1000 artificial samples. γPIB is the rate of growth of GDP.

TABLE 6
CAUSALITY TEST

Null hypothesis	F-statistic	Probability
γPIB does not granger cause Efficiency	0.235	0.87
Efficiency does not granger cause γPIB	2.36	0.09

γPIB is the rate of growth of GDP.

growth of GDP.[9] Furthermore, the results for the low efficiency in the period of former President Allende discussed earlier, suggest that agents may also anticipate political cycles.

5. Conclusions

In this paper, we have estimated an inefficiency measure of the transformation of human capital into earned income. We found that on average in the period 1957-1998, this inefficiency was close to 25% and in the last years (since 1990) this inefficiency falls to almost 20% on average. We also empirically showed that these measures are invariant to omission of relevant variables.

The variance decomposition of the compound residual also gives interesting results: Half of the variability in income usually attributed to heterogeneity and underspecification may be due to inefficiency among individuals.

Most of the variability of the average inefficiencies among individuals are unexplained with the variables available in the data base. Notwithstanding, we found that healthier workers are more able to reach the frontier so workers on industry, financial services, and construction sectors are. Also schooling of the mother in law helps to reach the frontier, even though this last effect is not strong, this would suggest that social factors or "networks" are important.

Finally using correlation measures and Granger causality tests, we found that there is a statistical precedence of the inefficiency measure to the rate of growth of GDP. We postulate that this causality implies a reverse economic causality: in an environment of forward looking agents negotiating salaries, an expected decrease in the rate of growth of GDP causes a fall in the level of salary (because of the less degree of worker negotiation power), beyond the level that would be implied by the human capital accumulation.

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9 We also performed Granger causality tests between efficiency and the unemployment rate, but no evidence of causality were found.

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APPENDIX

FIGURE 1
EFFICIENCIES OVER TIME

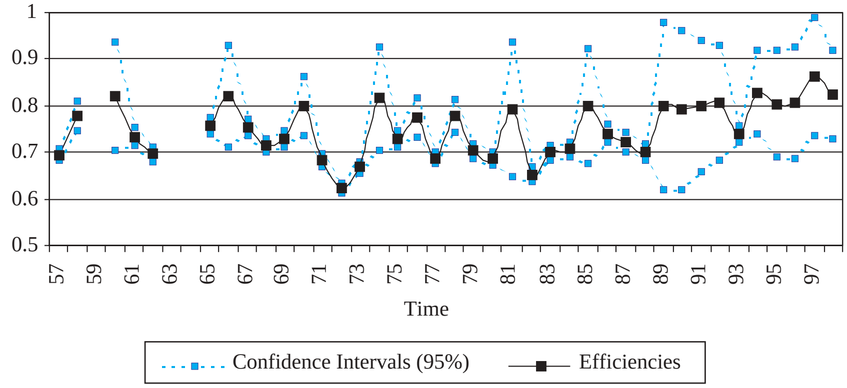

FIGURE 2
EFFICIENCES AND RATE OF GROWTH OF GDP