The economic return to vocational high schools in Chile

June 14, 2013

Abstract

This paper estimates the economic returns to vocational secondary education in Chile. Using administrative data we link individual salaries in 2010 (ages 24 to 27) with the type of secondary education each person attended in 2001. Adopting a generalized Roy model with local supply variables as exclusion variables, we identify the causal effect of attending vocational education on salaries. We report positive return to vocational education. Specifically, our estimated treatment on the treated is USD $232 per month. In addition, we estimate the effect of a policy that increases the local supply of vocational education. Our results show that those induced to attend vocational education as a result of this policy would face a return of USD $180.6 per month. Finally, we consider the different categories of vocational education. We report significant and positive returns for four of the five categories of vocational education in Chile, with returns ranging between USD $114 and USD $447 per month. These results have important consequences for the design of educational policies in the region. Vocational secondary schools might represent the best alternatives for many talented high school students.

JEL-Classification: I21, C31, J31

Keywords: Returns to education, Vocational Education, Marginal Treatment Effect.
1 Introduction

There is a large literature estimating the returns to education for developed countries. Unfortunately, there is much less work focused on the different returns to secondary vocational education in comparison with comprehensive education. This last literature is even smaller for developing countries. In fact, as far as we know, there is no formal evidence about the benefits or costs of attending secondary vocational education for Latin America.

This paper presents new evidence and insights for Chile, a medium-income country in the above mentioned region. It provides the first causal evidence of the economic returns to vocational education and its different categories. In addition, we motivate and present the economic returns for those individuals induced to attend vocational education by an increase in the number of vocational schools. This paper uses a unique data, that links type of education in high school in 2001 to salaries in 2010, we make use of the generalized Roy model to estimate these returns.

Our findings for Chile show positive returns to vocational education and most of its categories. This is consistent with previous studies on this topic. For the United States, Bishop and Mane (2004), as well as Meer (2007) found positive effects on salaries for people attending vocational education. Bishop and Mane (2004) show an increase in the premium wage for graduates of vocational education over the years due to the need that businesses have of skilled employees. Meer (2007) considers technical and business components in transcripts in his estimation that might oversimplify the differences between different areas. Positive evidence has also been found in other countries. For example, Newhouse and Suryadarma (2011) find positive effects on wages in Indonesia, while Moenjak and Worswick (2003) find positive returns in Thailand. On the other hand, other studies show no effect of vocational education on wages. For example, Malamud and Pop-Eleches (2010) show that potential benefits of vocational schools in Romania are driven by selection bias. Additionally, Arellano and Braun (1999) and Sapelli (2009) show similar returns to vocational education and comprehensive education in Chile, but their results do not correct for selection bias and unobserved heterogeneity as we do.

In Chile, secondary vocational education represents 33.2% of total enrollment. In contrast, this type of education represents on average 44% of the total enrollment in secondary education in OECD countries. Based on this information, a policy maker could pursue to increase the number of vocational education schools in Chile. Nevertheless, we do not know how the increase

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1 See Card (1999) and Meghir and Rivkin (2011) for surveys.
2 "Education at a Glance 2012", OECD. Alternative sources of information define a fraction in the order of 40%, all below the OECD average.
of vocational education schools would affect the salaries of those individuals induced to attend vocational education after this policy. There is no direct answer because of the lack of studies that analyze the causal effect of attending vocational education. This paper gives an answer to this issue.

In addition, the difference between comprehensive and vocational education is relevant due to the fact that most of the students do not continue tertiary studies, therefore, secondary education is the only training they will have to enter the labor market. In fact, Bassi and Urzua (2010) show that 34% of those who attended secondary comprehensive education do not continue tertiary studies, and just half of those who continue their studies finish them. In addition, 58% of those who attended vocational education do not continue tertiary studies and less than half of the remaining 42% finish their studies. Consequently, vocational and comprehensive education offer different educational paths.

In spite of the relevance of vocational education, little has been written about it in Chile. A recent effort to study the condition of vocational education was performed by a presidential committee in 2008 which concluded, among other things, that Chile need to provide stable funding for vocational education (MINEDUC, 2009). In line with this, the Chilean fiscal budget for 2012 considered US $45 million for equipment for vocational education. Nonetheless, there is neither formal evidence about the effectiveness of this type of education in the achievement of labor market insertion nor a guidance to know which category of vocational education should be supported.

The paper organizes as follow. The following section briefly describes the Chilean education system. The third section develops the econometric and decision model that motivates the parameters we estimate. Section four presents the data we use. Then we present our results, and finally the conclusion.

2 The chilean secondary education system: a brief description

In Chile, seventh grade students (and their families) have to decide between attending comprehensive and vocational education. These alternatives are not only different in terms of contents, but they also offer different educational paths. Moreover, vocational education focuses on developing skills for a good insertion in the labor market (MINEDUC, 2009).

37% of the individuals in our data, which is described later in section 4, attended vocational
education in 2001. Table 1 shows that the average number of vocational and comprehensive schools varies among regions. For example, the municipalities in the third region have on average more vocational schools than comprehensive schools. This variation in the offer of secondary education among municipalities determines what are the possibilities of studies in secondary education for each individual. The difference in enrollment in vocational education among regions is based on the differences in availability of vocational schools (column 3). This fact will be relevant for our empirical strategy.

A reform to secondary education in Chile was approved in 1998. It established a common curriculum until tenth grade for both kinds of education, the comprehensive and the vocational one. Therefore, specialized studies start in eleventh grade in vocational education high schools. Thereafter, there have been reforms have focused on increasing the match and interaction of vocational education with the current needs of the labor market.

3 Econometric Model and Treatment Parameters

We model economic returns to secondary vocational and comprehensive education using a two sector Roy model (Roy, 1951). This model establishes the existence of two potential outcomes for each individual. This set-up has been extensively used in economics to evaluate the economic returns to education (Carneiro, Heckman, and Vytlacil, 2011, Heckman and Vytlacil, 2007). Let \( Y_1 \) be the potential monthly average wage if the individual were to attend vocational secondary education, and \( Y_0 \) be the potential monthly average wage if the individual were to attend comprehensive secondary education. We define potential outcomes as

\[
Y_1 = \mu_1(X) + U_1 \quad \text{and} \quad Y_0 = \mu_0(X) + U_0
\]

with \( \mu_1(x) = E[Y_1|X = x] \) and \( \mu_0(x) = E[Y_0|X = x] \) where \( X \) denotes the vector of observed variables and \((U_1, U_0)\) represent the unobservables. We assume \( U_1 \not\perp U_0|X \). Hence, economic return to vocational education is \( Y_1 - Y_0 = \mu_1(x) - \mu_0(x) + U_1 - U_0 \).

The individual’s decision between vocational and comprehensive secondary education is modeled by a latent variable discrete choice model. Let \( I_V \) be the net benefit of attending vocational secondary education, defined as
\[ I_V = \mu_V(Z) - \nu \]  

(2)

Where \( Z \) represents the observed variables and \( \nu \) the unobserved unobserved component, which is assumed to be a continuous random variable with a strictly increasing cumulative distribution function \( F_\nu(\cdot) \). Therefore, an individual chooses to go to secondary vocational education \((V = 1)\) if \( I_V \geq 0 \) and secondary comprehensive education \((V = 0)\), otherwise. Let \( U_V = F_\nu(\nu) \) which is uniformly distributed by construction. Let \( P(z) \) denote the probability of choosing secondary vocational education \((V = 1)\) conditional on \( Z = z \), we can show that \( P(z) = Pr(V = 1|Z = z) = F_\nu(\mu_V(z)) \) and that the individual chooses to attend vocational education iff \( P(Z) \geq U_V \).

This is the model of essential heterogeneity in which there may be sorting on the gain \((\text{Cov}(\beta, D) \neq 0)\). This a phenomenon distinct from selection bias and in this context instrumental variables may not identify a causal parameter. Given that this assumption is testable (Heckman, Schmierer, and Urzua, 2010) we verify it in our data.

The usual treatment parameters in the treatment effect literature can be defined within this framework. The average treatment effect of attending vocational education is \( ATE(x) = E(Y_1 - Y_0|X = x) = \mu_1(x) - \mu_0(x) \). In addition, the treatment on the treated is \( TT(x) = E(Y_1 - Y_0|V = 1, X = x) = \mu_1(x) - \mu_0(x) + E(U_1 - U_0|V = 1, X = x) \). Finally, following Heckman and Vytlacil (1999, 2005), we define the marginal treatment effect \( (MTE) \) as:

\[ MTE(x; u_V) = E(Y_1 - Y_0|X = x, U_V = u_V) \]  

(3)

This parameter represents the average gain for those individuals indifferent between attending vocational or comprehensive education when \( Z \) is such that \( P(Z) = u_V \). This parameter is estimated using local instrumental variable method developed in Heckman and Vytlacil (2005) and Heckman, Urzua, and Vytlacil (2006). In this method, \( MTE \) is identified by differentiating \( E(Y|X = x, P(Z) = p) \) with respect to \( p \) over the common support of \( P(Z) \). Since \( U_V \sim Unif[0, 1] \), calculating \( MTE \) for different values of \( U_V = u_V \) shows the returns over quantiles of the unobserved component of the index model. \( MTE \) for those individuals with low values of \( U_V \) corresponds to the average return to those that have an unobservable component that make them more prone to attend vocational education. In contrast, \( MTE \) for individuals
with high values of $U_V$ is the average economic return for those with an unobserved component that make them unlikely to go to vocational education. The papers previously mentioned redefined treatment parameters as a function of $MTE$. See Heckman, Urzua, and Vytlacil (2006) for the formulae linking the $MTE$ to different treatment parameters.

In general, $ATE$ and $TT$ are relevant treatment parameters since they show economic returns for different groups of population. Nevertheless, we can define a specially relevant parameter from a public policy perspective. In fact, whenever a policy maker evaluates the return for a specific policy (e.g. to build vocational schools) she is usually looking for the return of those affected by it. This motivates introducing the policy relevant treatment effect ($PRTE$). This parameter was first introduced by Heckman and Vytlacil (2001) and reformulated in its marginal version in Carneiro, Heckman, and Vytlacil (2010).

Let $V^*$ be the decision made by individuals after introducing a new policy, with $V^* = 1$ if after the policy the individual chooses vocational education and $V^* = 0$ if he chooses comprehensive education after the policy. Let $P^*$ be the probability of $V^* = 1$. Let $V^* = 1[\gamma = U_V\gamma]$, and $Y^* = V^*Y_1 + (1 - V^*)Y_0$, where we assume that the introduced policy modifies decisions but it does not change the outcome distribution. Heckman and Vytlacil (2001) show that the average effect per net person that changes its treatment status is the policy relevant treatment effect ($PRTE$), defined when $E(V) \neq E(V^*)$:

$$
\frac{E(Y|\text{Alternative policy}) - E(Y|\text{Baseline policy})}{E(V^*|\text{Alternative policy}) - E(V|\text{Baseline policy})} = \frac{E(Y^*) - E(Y)}{E(V^*) - E(V)}
= \int_0^1 MTE(u_V)\omega_{PRTE}(u_V)du_V
$$

where

$$\omega_{PRTE} = \frac{F_{P^*}(u_V) - F_{P^*}(u_V)}{E_{F_{P^*}}(P) - E_{F_{P}}(P)}$$

where $F_{P^*}(P)$ y $F_{P}(P)$ are the distributions of $P^*$ y $P$, respectively. The $PRTE$ gives us an interpretable parameter from a public policy perspective and its value depends on which policy we are evaluating. As Carneiro, Heckman, and Vytlacil (2010) mentioned this parameter is not identified without full common support of the propensity score. Nevertheless, it is possible to identify a marginal version of this parameter. In fact, there are a set of policies that can be indexed by the scalar variable $\alpha$. For each of these policies we define $PRTE(\alpha)$, then we can take limit as $\alpha$ gets close to zero. Formally, the parameter of interest is

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3 We keep conditioning on $X$ implicit.

4 An example of these policies is a change of one of the variables in $Z$ ($Z_k = Z_k + \alpha$). In our case it could be an increase in the number of vocational secondary schools. Another policy is to change $P$ such that $P^* = P + \alpha$.
\[
M_P R T E(\{F_\alpha\}) = \int_0^1 MTE(u) \omega_{M_P R T E}(u; F_\alpha)
\]

with \( \omega_{M_P R T E}(u; F_\alpha) = -\frac{\partial}{\partial \alpha} F_0(u) \frac{\partial}{\partial \alpha} E_{F_0(u)} \)

Depending on which policy we consider, the weights \( \omega_{M_P R T E} \) change. This parameter can be used to answer economically relevant and well posed questions. For example, we can consider an increase in the supply of vocational schools. This parameter addresses an important issue for countries where the limited supply of vocational high schools is fueling the public policy discussion. Formally, let us consider a policy that changes the level of one component of \( Z \), in other words, under the alternative policy we will have:

\[
Z_k^* = Z_k + \alpha
\]

where \( Z_k \) is the \( k \)th element of \( Z \). The MPRTE is the right parameter for cost-benefit analysis since it gives us the return for those individuals affected by a given policy. In addition, we consider two other policies that affect the probability of enrolling in vocational education. First, let us consider an increase of \( \alpha \) in the probability \( P \) of attending a vocational school, \( P_\alpha = P + \alpha \). Second, let us consider a proportional change in the probability such that \( P_\alpha = (1 + \alpha)P \).

4 Empirical Implementation

4.1 Data

Our data links information from administrative records on test scores in 2001, tertiary education enrollment between 2007-2010 and earnings on 2010. Test scores come from SIMCE\(^5\) 2001. SIMCE is a standardized battery of tests administered to students of a specific grade level, which rotates yearly between 8th and 10th grades, and is also administered to 4th graders every year since 2005. The aim of SIMCE is to measure students’ degree of learning in a number of subjects of the curriculum. Information of tertiary education enrollment comes from administrative data from the Ministry of Education. Earning information is obtained from the Ministry of Labor, specifically, from the Unemployment Insurance System data base. This information records monthly earnings for workers with formal contracts.\(^6\) Finally, tertiary studies records are from

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\(^5\)SIMCE stands for Sistema de Medicion de la Calidad de la Educacion

\(^6\)We do not observe earnings for individuals in the informal sector
Ministry of Education of Chile.

From a total of 149,431 people (ages 24 to 27), we end up with 72,137 people for our estimation. We leave out from our data 40,405 people who attended schools with two or more types or categories of education (hybrid schools), because we cannot identify if they attended a comprehensive or vocational course. Table 3 shows that this group has lower test scores and worse family background in comparison with people who attended comprehensive or vocational education schools. Given our data restrictions we are not able to disentangle any particular bias of leaving this group out of our data.

In addition, we leave out of our data people who attended tertiary education in 2010 because they are not completely integrated in the labor market. Table 4 shows that the deleted observations correspond to individuals with better family background and better standardized test scores in comparison with the rest of our sample (columns 1 and 2). Due to the fact that 71.7% of those enrolled in tertiary education in 2010 attended comprehensive schools this might bias our results against this group. Nevertheless, people still enrolled in tertiary studies in 2010 have lower scores and family background if we compare them with people enrolled in tertiary education in 2009 who are not enrolled in 2010. A 73.5% of this group attended comprehensive schools. Therefore, we are not considering the less able of the tertiary students who attended comprehensive education. This does not rule out bias but it should reduce it.

Summary statistics of the variables in our model are presented in table 5. It shows that those who attended vocational education have on average higher salaries in 2010 in comparison with those who attended Comprehensive Education. In addition, the first group has lower SIMCE scores and mother’s year of schooling in comparison with those attending Comprehensive Education in 2001. Finally, men are a higher proportion in Vocational Schools. These differences show no causal relationship but indicate the importance of controlling adequately for this characteristics.

**Sources of Instruments:** In order to identify our model, we utilize data on local availability of vocational schools. We implement our econometric model using additional data from the Ministry of Education of Chile. This provides a source of exogenous variation (Card, 2001). We consider local supply of each type of secondary education at level of municipality. Specifically, the number of vocational and comprehensive schools, and the proportion of enrollment that vocational education represents over the total enrollment in secondary education at municipality level. These are our exclusion variables in the index model presented above. Figure 1 shows the variability of the number of vocational schools at municipality level for the north regions of

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726% of those attending tertiary education in 2010 were vocational education students.
Chile. The white municipalities have no vocational education schools, and the black ones have between four and fifteen schools.\(^8\) This variability helps us to identify the parameters described in the previous section.

A possible concern with the instrument is that the location of vocational education schools in 2000 is guided by the returns to this kind of education among the municipalities. This would violate the independency assumption of the instruments variables with respect to the outcome. Nevertheless, the outcome that we are analyzing has ten years of difference with the location of schools. Therefore, individuals could have move from their original municipality or the labor market conditions could have changed over the years. In addition, we address this concern controlling by monthly average local salaries in 2000 for individuals who attended vocational education schools. For this purpose we use data from CASEN that is a nationally representative survey.\(^9\)

For each type of secondary education, table 5 shows the average number of months of unemployment or informal employment in 2010. This table shows that for those who attended comprehensive education the number of months without a formal job is higher (1.8 months) in comparison those who attended vocational education. Unemployment or informal work is an important fact for the cohort of individuals in our data. In fact, figure 2 shows that 21\% of those who attended comprehensive school did not either study nor work in the formal sector between January 2010 and May 2011.

### 4.2 Empirical Specification

In our empirical work we proceed by imposing additional assumptions. We assume that \((X, Z)\) are independent of \((U_0, U_1, U_V)\). This is a typical assumption in instrumental variables literature. Under this assumption \(MTE\) is additively separable in \(X\) and \(U_V\). Moreover, this allows us to identify the \(MTE\) over the unconditional support of \(P\). In addition, we impose a linearity assumption over \(\mu_1(X), \mu_0(X) y \mu_V(Z)\): \(\mu_1(X) = X\beta_1, \mu_0(X) = X\beta_0 y \mu_V(Z) = Z\gamma\). In this case,

\[
E(Y|X = x, P(Z) = p) = x\beta_0 + px(\beta_1 - \beta_0) + K(p),
\]

where \(K(p) = E(U_1 - U_0|V = 1, P(Z) = p)\) can be estimated non parametrically. Hence,

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\(^8\)The full set of results can be obtained upon request from authors.

\(^9\)We drop 610 individuals whose municipality is not in CASEN.
using standard semiparametric techniques we estimate $E(Y|X = x, P(Z) = p)$ and its derivatives with respect to $p$.

Given that, we estimate $MTE$ as,

$$
\hat{MTE}(X = x, U_V = u_V) = x'(\hat{\beta}_1 - \hat{\beta}_0) + \frac{\partial K(p)}{\partial p}_{|_{p=u_V}}
$$

As we mentioned before, treatment parameters can be estimated as a weighted average of $MTE$ and a weight scheme. Nevertheless, because we usually do not have full support $ATE$ cannot be estimated. On the other hand, due to the fact that $MPRTE$ has positive weights just for positive values of $P(Z)$ on the common support it does not require full support on its estimation. In order to estimate it, it is necessary to calculate weights for each evaluated policy mentioned before.

## 5 Results

We begin analyzing the returns to vocational education using OLS. We report different specifications for this return on table 8 (columns 1 to 5). We notice that in all the estimations vocational education has a positive and statistically significant coefficient, and from the change in the sign of the coefficient associated with mother’s year of schooling we can see that it is important to control for the average test score in SIMCE. Nevertheless, it is not enough to argue causal effect from regression in column 5, because SIMCE is observed after being treated by the type of school for two years.

As described in section 3, the propensity score plays an important role in the identification of the treatment parameters defined in our model. Table 6 presents the results for propensity score estimation. This shows the marginal effects from the Probit model based on equation 2. In line with what we expected, a higher percentage of total enrollment that vocational education represents in each municipality increases the probability of attending that type of education.

An important requirement for the identification of the treatment parameters is the support of the propensity score. Figure 4 shows almost full support for propensity score. In fact, the common support goes between 0.0062 and 0.9854. This suggests that we can identify the $TT$ but probably not $TUT$ and $ATE$ (Heckman and Vytlacil, 1999).

Our model for decision making and the impact of vocational education allows for sorting on unobserved gains. We test selection on gains using a test developed in Heckman, Schmierer, and Urzua.
The idea is that $K(P)$ in equation 5 should be linear in $P(Z)$ when there is no selection on gains. Therefore, we test whether the coefficients associated with polynomial terms of order higher than one are jointly equal to zero. Results for this test are presented in table 7. Each column estimates equation 5 using a different maximum polynomial order of $P(Z)$ to approximate $K(P)$. In addition, we use the methodology developed in Romano and Wolf (2005) to test multiple hypothesis at the same time and so correct the critical p-value. Table 7 shows the rejection of the null hypothesis for the polynomials with maximum orders of three, four and five at 99 percent of confidence. This result has consequences over the interpretation that we can make about the instrumental variable methodology in this context. Specifically, IVs could not capture correctly the returns to vocational education in this context. This fact has been pointed out by Heckman, Urzua, and Vytlacil (2006), they show that under the case of selection on gains, instrumental variables do not capture the causal effect. The last column in table 8 shows the estimation using instrumental variables in our context. The results show that technical vocational education has a return of USD $31.24 (column 6). As we show later, instrumental variable estimation underestimates the returns to vocational education.

The estimation of the $MTE$ using a semiparametric approach is done over the common support of the propensity score. We estimate parameters of $E(Y|X, P(Z) = p)$ detailed in equation 5. To do so, we approximate $K(p)$ using a polynomial in $P(Z)$ of order three.\footnote{Given that, we obtain $	ilde{Y} = Y - \hat{\alpha}_0 - X' \hat{\beta}_0 - X'(\hat{\beta}_1 - \beta_0)P(Z)$. Then the problem is reduced to the estimation of $K(p)$, where $K(p)$ can be interpreted as the unconditional expected value $E(\tilde{Y}|P(Z) = p)$. Finally, we estimate the derivative of $K(p)$ with respect to $p$ using a quadratic local regression. $MTE$ is evaluated in 26 points equally distributed between 0 and 1.} Figure 5 shows the estimation of the $MTE$ with 90% confidence bands. It shows that individuals with unobservables that make them more likely to go to vocational education (low values of $U_V$) have positive returns to attend vocational education. In contrast, individuals with high values of $U_V$ have non positive return to attending vocational education. This return is over USD $300 for some values of $U_V$, but it is not significantly different from zero for other values. Therefore, there is an important heterogeneity among individuals with different values for the unobservable variable. This motivates the importance of considering the right margin when we evaluate an aggregate measure of the return to vocational education. In fact, some measures like $ATE$ equally weight each individual, but other treatment parameters give more importance to certain ranges of the unobservable variable.

Using the weights for the $MTE$ defined in Heckman, Urzua, and Vytlacil (2006) we estimate the $TT$. Table 9 shows that this parameter is positive and statistically significant at 95% of
confident with a value of $US 232.7.\textsuperscript{11} This result is the first causal evidence of the returns to individuals who attended vocational education and it shows the relevance of this type of education. It is also important given the low percentage of students in who attended vocational education in comparison with other OECD countries.

As we mentioned before, a relevant question are the returns to individuals induced to enroll in vocational education by an increase in the number of schools of this kind of education. This is specially relevant at the light of the low enrollment in vocational education in Chile in comparison to other OECD countries.\textsuperscript{12} This fact could be used to argue that Chile needs an expansion in the number of vocational education schools. The parameter needed to answer this question is more specific than the treatment on the treated (TT) parameter, because people that would enroll in vocational education in response to this policy might face different returns in comparison to those who are already attending vocational education. Indeed, $MPRTE$ is the correct parameter to analyze the effect over the compliers of such a policy. In particular, we consider three potential policies: i) An increase in the number of vocational schools in each municipality $(Z^k = Z^k + \alpha)$, ii) A constant increase in the probability of attending vocational education $(P_\alpha = P + \alpha)$, and iii) a proportional increase in the probability of attending vocational education $(P_\alpha = (1 + \alpha)P)$. Figure 6 shows each weight scheme for $MPRTE$. The results for the $MPRTE$ for these policies are presented in table 9. It shows that the marginal return to these policies is positive and statistically significant. The returns estimation for a marginal increase in the number of vocational education schools is USD $180.6. This result should be taken into account in the evaluation of public policies related to the supply of vocational education schools.

Additionally, we calculate the $MPRTE$ excluding from our data people who attended private schools.\textsuperscript{13} In Chile, for those attending vocational education schools attending a private institution is not an option. Therefore, an increase in the supply of vocational education will probably affect people attending public or subsidized-private schools. Figure 7 shows the $MTE$ estimation, and the last rows of table 9 shows the $MPRTE$ for this subsample. In line with our previous results, the calculated $MTE$ shows the importance of taking into account heterogeneity. In this case the $TT$ is USD $189.4 and statistically significant. Table 9 also shows that the $MPRTE$ is positive and significant for every evaluated policy with values going from USD $91.4 to USD $121.2. Individuals that after an increase in the number of vocational schools enroll in vocational education face a return of USD $106.8. Therefore, our main results are

\textsuperscript{11}The minimum wage was set in US $318 between July 2010 and June 2011.
\textsuperscript{12}Countries like Germany and France have 51.5% and 44.3% of secondary vocational education enrollment (OECD, “Education at a Glance 2012”).
\textsuperscript{13}We exclude 13,352 people from our data.
robust to the change in the sample we consider.

In Chile, secondary vocational education has five categories, and each of them has specialties within a common area of knowledge. The categories are: i) commercial, ii) industrial, iii) technical, iv) agricultural, and v) maritime. In this paper we simplify the decision the that individuals made by assuming a model of binary decision between attending vocational or comprehensive education (equation 2), therefore grouping all the categories of vocational education in one. This is an assumption similar to the one made by Willis and Rosen (1979) and Carneiro, Heckman, and Vytlacil (2011). They modeled the decision between going to college or not, but not the decision of how many years to attend to college. In our case we adopt a strategy similar to Willis and Rosen (1979) since we control for each category in vocational education.14 This allows us to compute treatment parameter for each category in vocational education. In particular, we estimate $MTE$ conditional on each type of education using,$^{15}$

$$MTE_j(X = x, U_V = u_V, D_V = j) = (\delta_{1,j} - \delta_{0,j}) + x' (\beta_1 - \beta_0) + \frac{\partial K(p)}{\partial p} \bigg|_{p = u_V}$$  

where $D_V = j$ if the individual attended category $j$ of vocational education and $\delta_{1,j} - \delta_{0,j}$ is the estimation of the dummy associated to category $j$.

Figure 8 shows the estimated $MTE$ and its 90 percent confidence interval for technical vocational education. Finally, table 10 shows the treatment parameters for each category. $TT$ is positive and statistically significant at 95% of confidence for every category with exception of industrial vocational education, with values ranging from USD $114.5 to USD $447.3. It shows the heterogeneity among categories of vocational education. On the other hand, $MPRTE$ is positive and statistically significant for each category, with exception of the maritime one. The returns estimation for a marginal increase in the number of vocational education schools goes from USD $435.6 for the maritime vocational education to USD $102.8 for the commercial vocational education.

6 Concluding remarks

In this paper we analyze the economic return to vocational education compared with comprehensive education. Through the use of a generalized Roy model this paper estimates the causal relation between attending vocational or comprehensive education and the earnings of individuals. The model controls for the number of years attended to college by dummmies.14 Willis and Rosen (1979) control for the number of years attended to college by dummmies.15 This follows the same idea in 4.2. The only difference is that this version includes a set of dummmies controlling for each type of vocational education as a part of $X$. 

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effect of secondary vocational education on labor market outcomes in Chile. Our empirical strategy uses new data, which links salaries to educational records and supply-level data as source of exclusion restriction to estimate the return to vocational education in Chile. Our findings show positive returns to vocational education relative to the alternative, namely comprehensive high schools. In particular, the treatment on the treated is USD $232. When we consider the different categories of vocational education we show that most of these categories have positive and significant returns ranging between USD $114 and USD $447. Previous evidence for Chile showed similar returns for comprehensive and vocational education and it did not distinguish among categories of vocational education (Arellano and Braun, 1999, Sapelli, 2009). Therefore, our results are the first causal evidence of the returns to vocational education and its categories in Chile. Additionally, our evidence supports previous evidence about the positive effects of vocational education in labor market outcomes in developing countries (Moenjak and Worswick, 2003, Newhouse and Suryadarma, 2011).

Using the test developed in Heckman, Schmierer, and Urzua (2010) we test and verify the presence of unobserved heterogeneity in our model. This has important implications for the future estimation of returns to education in Chile and it calls to be cautious at the moment of interpreting previous evidence based on instrumental variables approach. In fact, in the context of unobserved heterogeneity, instrumental variables approach is no longer a good method to estimate a causal effect. In fact, we show that instrumental variables suggest smaller returns to vocational education. Therefore, the use of instrumental variables might lead to misleading conclusions about the returns to vocational education.

Finally, we analyze the effects of an increase in the local supply of vocational high schools. This is a well-posed and economically relevant question that is not answered by the classic treatment parameters. In particular, using the \( MPRTE \) parameter developed in Carneiro, Heckman, and Vytlacil (2011), we evaluate the effects of two policies. A marginal increase in the number of vocational schools in each municipality and a policy that increases the probability of attending vocational education. This paper is the first using this methodology in a developing country.

Our estimation shows that individuals affected by these policies would face positive returns going from USD $174 to USD $181, depending on the particular policy. When we look at the different categories of vocational education, this result remains the same for most of the categories. For example, individuals induced to attend commercial vocational education after being exposed to a marginal increase in the supply of vocational schools face a return of USD $102 in comparison with the alternative of attending comprehensive education.

These results open the question of the lack of secondary vocational education in Chile in
relation to OECD standards. Vocational education represents an important alternative to many students in Chile and the region, and there are some public policies that should be considered.
References


# Tables and Figures

**Table 1:** Average number of schools and average percentage of enrollment of each type of education in municipalities per region of Chile

<table>
<thead>
<tr>
<th>Region</th>
<th>Average Number of Comprehensive Schools</th>
<th>Average enrollment in Comprehensive Education</th>
<th>Average Number of Vocational Schools</th>
<th>Average enrollment in Vocational Education</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.1</td>
<td>70.1</td>
<td>2.9</td>
<td>29.9</td>
</tr>
<tr>
<td>2</td>
<td>4.4</td>
<td>60.7</td>
<td>2.8</td>
<td>39.3</td>
</tr>
<tr>
<td>3</td>
<td>2.6</td>
<td>64.6</td>
<td>3.1</td>
<td>35.4</td>
</tr>
<tr>
<td>4</td>
<td>4.1</td>
<td>83.3</td>
<td>1.9</td>
<td>16.7</td>
</tr>
<tr>
<td>5</td>
<td>6.2</td>
<td>79.3</td>
<td>2.4</td>
<td>20.7</td>
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<td>2.8</td>
<td>88.6</td>
<td>1.1</td>
<td>11.4</td>
</tr>
<tr>
<td>7</td>
<td>2.8</td>
<td>70.0</td>
<td>2.5</td>
<td>30.0</td>
</tr>
<tr>
<td>8</td>
<td>2.7</td>
<td>82.0</td>
<td>1.8</td>
<td>18.0</td>
</tr>
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<td>9</td>
<td>2.4</td>
<td>72.3</td>
<td>2.2</td>
<td>27.7</td>
</tr>
<tr>
<td>10</td>
<td>2.3</td>
<td>71.6</td>
<td>2.1</td>
<td>28.4</td>
</tr>
<tr>
<td>11</td>
<td>1.0</td>
<td>83.1</td>
<td>0.8</td>
<td>16.9</td>
</tr>
<tr>
<td>12</td>
<td>2.0</td>
<td>80.8</td>
<td>1.3</td>
<td>19.2</td>
</tr>
<tr>
<td>13</td>
<td>10.9</td>
<td>67.8</td>
<td>6.8</td>
<td>32.2</td>
</tr>
</tbody>
</table>

Note: Administrative division in 2000. Source: Author’s calculation based on Ministry of Education of Chile dataset.

**Table 2:** Definitions of the variables used in the empirical analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y$</td>
<td>Monthly average wage in 2010</td>
</tr>
<tr>
<td>$V = 1$</td>
<td>If the individual attended secondary vocational education in tenth grade</td>
</tr>
<tr>
<td>$X$</td>
<td>Sex, Mother’s years of schooling, Average SIMCE scores in 2001 (10th grade) and regional dummies, Local salaries for vocational school graduates in 2000 ($Y,V_{2000}$).</td>
</tr>
<tr>
<td>$Z\setminus X$</td>
<td>Number of vocational schools at local level (municipality), number of comprehensive high schools at local level and proportion of enrollment that vocational education represents over the total at municipality level.</td>
</tr>
</tbody>
</table>
Table 3: Mean difference test for students who attended to hybrid schools in comparison to the ones who attended comprehensive or vocational education

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
<td>0.1</td>
<td>-0.03***</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>SIMCE language 2001 (10th grade)</td>
<td>231.8</td>
<td>254.8</td>
<td>239.2</td>
<td>-23.0</td>
<td>-7.35***</td>
</tr>
<tr>
<td></td>
<td>(43.1)</td>
<td>(50.8)</td>
<td>(43.2)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>SIMCE mathematics 2001 (10th grade)</td>
<td>225.1</td>
<td>249.5</td>
<td>233.1</td>
<td>-24.3</td>
<td>-7.95***</td>
</tr>
<tr>
<td></td>
<td>(38.8)</td>
<td>(54.0)</td>
<td>(41.1)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Mother’s years of schooling</td>
<td>8.6</td>
<td>11.0</td>
<td>9.0</td>
<td>-2.4</td>
<td>-0.35***</td>
</tr>
<tr>
<td></td>
<td>(4.3)</td>
<td>(5.1)</td>
<td>(4.4)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Father’s years of schooling</td>
<td>8.7</td>
<td>11.3</td>
<td>9.0</td>
<td>-2.6</td>
<td>-0.27***</td>
</tr>
<tr>
<td></td>
<td>(4.2)</td>
<td>(5.3)</td>
<td>(4.3)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Average number of unemployment or informality work in 2010</td>
<td>5.0</td>
<td>5.8</td>
<td>4.7</td>
<td>-0.8</td>
<td>0.33***</td>
</tr>
<tr>
<td></td>
<td>(5.0)</td>
<td>(5.0)</td>
<td>(5.0)</td>
<td>0.0</td>
<td></td>
</tr>
<tr>
<td>Average wage in 2010</td>
<td>367.2</td>
<td>383.5</td>
<td>401.8</td>
<td>-16.3</td>
<td>-34.62***</td>
</tr>
<tr>
<td></td>
<td>(393.7)</td>
<td>(475.0)</td>
<td>(413.5)</td>
<td>0.0</td>
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</tr>
<tr>
<td>Number of Observations</td>
<td>40405</td>
<td>42383</td>
<td>30366</td>
<td>82788</td>
<td>70771</td>
</tr>
</tbody>
</table>

Note: In this table we dropped individuals enrolled in tertiary education in 2010. Standard errors in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1.
(1): People who attended hybrid schools
(2): People who attended comprehensive education schools
(3): People who attended vocational education schools
(4): Difference between (1) and (2).
(5): Difference between (1) and (3).
Table 4: Mean-difference tests. Sample of all students in 2010 vs different subsamples.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage of comprehensive</td>
<td>71.7</td>
<td>56.5</td>
<td>73.5</td>
<td>15.2***</td>
<td>-1.9***</td>
</tr>
<tr>
<td></td>
<td>(45.1)</td>
<td>(49.6)</td>
<td>(44.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>0.5</td>
<td>0.5</td>
<td>0.5</td>
<td>0.02***</td>
<td>0.05***</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>(0.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIMCE language 2001 (10th grade)</td>
<td>274.5</td>
<td>248.2</td>
<td>276.0</td>
<td>26.3***</td>
<td>-1.5***</td>
</tr>
<tr>
<td></td>
<td>(47.3)</td>
<td>(48.4)</td>
<td>(47.9)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SIMCE mathematics 2001 (10th grade)</td>
<td>273.5</td>
<td>242.5</td>
<td>275.3</td>
<td>31.0***</td>
<td>-1.8***</td>
</tr>
<tr>
<td></td>
<td>(54.9)</td>
<td>(49.6)</td>
<td>(55.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother’s years of schooling</td>
<td>12.1</td>
<td>10.2</td>
<td>12.3</td>
<td>1.9***</td>
<td>-0.2***</td>
</tr>
<tr>
<td></td>
<td>(4.8)</td>
<td>(4.9)</td>
<td>(4.8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Father’s years of schooling</td>
<td>12.4</td>
<td>10.4</td>
<td>12.6</td>
<td>2.0***</td>
<td>-0.2**</td>
</tr>
<tr>
<td></td>
<td>(5.2)</td>
<td>(5.1)</td>
<td>(5.2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average number of unemployment or informality work in 2010</td>
<td>8.0</td>
<td>5.3</td>
<td>6.2</td>
<td>2.7***</td>
<td>1.8***</td>
</tr>
<tr>
<td></td>
<td>(4.8)</td>
<td>(5.0)</td>
<td>(4.7)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average wage in 2010</td>
<td>215.3</td>
<td>390.5</td>
<td>428.5</td>
<td>-175.2***</td>
<td>-213.2***</td>
</tr>
<tr>
<td></td>
<td>(367.3)</td>
<td>(449.5)</td>
<td>(527.3)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations</td>
<td>29083</td>
<td>75035</td>
<td>12418</td>
<td>104118</td>
<td>41501</td>
</tr>
</tbody>
</table>

Note: We dropped individuals who attended hybrid schools. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
(1): Individuals enrolled in tertiary studies in 2010.
(2): Sample excluding individuals enrolled 2010.
(3): Enrolled in 2009 but not in 2010.
(4): Mean difference between (1) and (2).
(5): Mean difference between (1) and (3).

Table 5: Summary Statistics by type of secondary high schools

<table>
<thead>
<tr>
<th></th>
<th>Comprehensive Mean</th>
<th>SD</th>
<th>Vocational Mean</th>
<th>SD</th>
<th>Mean Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average monthly Salary in 2010</td>
<td>316.5</td>
<td>447.6</td>
<td>385.1</td>
<td>412.3</td>
<td>-68.7***</td>
</tr>
<tr>
<td>Average Unemployment months in 2010</td>
<td>6.7</td>
<td>5.01</td>
<td>4.9</td>
<td>5.0</td>
<td>1.7***</td>
</tr>
<tr>
<td>Average SIMCE 2001 (10th grade)</td>
<td>261.5</td>
<td>49.8</td>
<td>240.1</td>
<td>38.9</td>
<td>21.4***</td>
</tr>
<tr>
<td>Mother’s years of schooling</td>
<td>9.3</td>
<td>6.5</td>
<td>7.2</td>
<td>5.5</td>
<td>2.1***</td>
</tr>
<tr>
<td>Sex</td>
<td>0.5</td>
<td>0.5</td>
<td>0.6</td>
<td>0.5</td>
<td>-0.09***</td>
</tr>
<tr>
<td>Percentage of Enrollment in tertiary studies in 2010</td>
<td>32.9</td>
<td>47.0</td>
<td>19.4</td>
<td>39.6</td>
<td>0.1***</td>
</tr>
<tr>
<td>N</td>
<td>63228</td>
<td></td>
<td>37717</td>
<td></td>
<td></td>
</tr>
<tr>
<td>%</td>
<td>62.3</td>
<td></td>
<td>37.7</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Sex equals 1 for men. Source: Unemployment Insurance System 2010 and SIMCE. *** p<0.01, ** p<0.05, * p<0.1.
Table 6: Schooling model: Vocational vs Comprehensive (Marginal effects).

<table>
<thead>
<tr>
<th>Controls(X)</th>
<th>Marginal Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local wage vocational education in 2000</td>
<td>-.0001 (0.00002)***</td>
</tr>
<tr>
<td>Sex</td>
<td>0.1003 (0.0039)***</td>
</tr>
<tr>
<td>Dummy of existence of data of mother’s schools</td>
<td>0.1508 (0.0060)***</td>
</tr>
<tr>
<td>Dummy of existence of data of mother’s schooling*Mother’s years of schooling</td>
<td>-0.0181 (.0005)***</td>
</tr>
<tr>
<td>Average SIMCE scores in 2001 (10th grade)</td>
<td>-0.0015 (0.00005)***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Instruments(Z)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Vocational Schools</td>
<td>.0029 (0.0006)***</td>
</tr>
<tr>
<td>Number of Comprehensive Schools</td>
<td>0.0027 (0.0003)***</td>
</tr>
<tr>
<td>Proportion of enrollment in vocational education over total enrollment</td>
<td>1.7676 (0.0209)***</td>
</tr>
<tr>
<td>Number of observations</td>
<td>72,137</td>
</tr>
<tr>
<td>F-test for instruments</td>
<td>4,093.22</td>
</tr>
</tbody>
</table>

Notes: This table reports the marginal effects for probit regression of vocational education attendance. We evaluate X, Z in average sample values, except for dummies in which case we evaluate the change from 0 to 1. Probit controls by region dummies. F-test for instruments was performed for linear regression.

Table 7: Test of linearity of E(Y|X, P = p) using polynomials in P.

<table>
<thead>
<tr>
<th>Degree of polynomial for model</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>p-value of joint test of nonlinear terms</td>
<td>0.1681</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Adjusted critical value (95% Confidence)</td>
<td></td>
<td>0.0126</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted critical value (99% Confidence)</td>
<td></td>
<td></td>
<td>0.0008</td>
<td></td>
</tr>
</tbody>
</table>

Note: We estimate E(Y|X = x, P(Z) = p) = xβ₀ + px(β₁ - β₀) + K(p) using a polynomial on P(Z) to approximate K(p). The size of the test is controlled using critical value constructed by the bootstrap method of Romano and Wolf (2005) using a 5 percent significance level.
Table 8: Estimation using OLS and IV.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vocational Education</td>
<td>18.13</td>
<td>30.06</td>
<td>15.57</td>
<td>24.80</td>
<td>42.56</td>
<td>31.24</td>
</tr>
<tr>
<td>(3.40)</td>
<td>(3.45)</td>
<td>(3.43)</td>
<td>(3.43)</td>
<td>(3.40)</td>
<td>(8.28)</td>
<td></td>
</tr>
<tr>
<td>Mother’s year of schooling</td>
<td>7.07</td>
<td>7.13</td>
<td>5.48</td>
<td>1.48</td>
<td>9.19</td>
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</tr>
<tr>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(0.39)</td>
<td>(5.68)</td>
<td></td>
</tr>
<tr>
<td>Dummy of existence of data of</td>
<td>-41.07</td>
<td>-38.20</td>
<td>-22.21</td>
<td>7.71</td>
<td>1.31</td>
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</tr>
<tr>
<td>mother’s schools</td>
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<td>(5.63)</td>
<td>(5.63)</td>
<td>(5.59)</td>
<td>(0.41)</td>
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</tr>
<tr>
<td>Sex</td>
<td>136.94</td>
<td>139.63</td>
<td>141.43</td>
<td>142.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3.33)</td>
<td>(3.31)</td>
<td>(3.27)</td>
<td>(3.34)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local wage vocational education in 2000</td>
<td>0.24</td>
<td>0.17</td>
<td>0.17</td>
<td></td>
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<td></td>
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<tr>
<td>(0.01)</td>
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<td>(0.01)</td>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
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</tr>
<tr>
<td>Average SIMCE score 2001</td>
<td></td>
<td></td>
<td></td>
<td>1.73</td>
<td>1.72</td>
<td></td>
</tr>
<tr>
<td>(10th grade)</td>
<td></td>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.04)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Returns in USD 2010. Exchange rate in December 2010 was 478.78 Chilean pesos per US dollar. Regressions (1)-(5) are estimated by OLS. IV estimation in (6) uses Propensity Score ($P$) as instrument.

Table 9: Semiparametric estimation for TT and MPRTE

<table>
<thead>
<tr>
<th></th>
<th>TT</th>
<th>$Z^k_\alpha = Z^k + \alpha$</th>
<th>$P_\alpha = P + \alpha$</th>
<th>$P_\alpha = (1 + \alpha)P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>232.7</td>
<td>180.6</td>
<td>181.1</td>
<td>174.4</td>
</tr>
<tr>
<td></td>
<td>(68.3)</td>
<td>(74.2)</td>
<td>(41.4)</td>
<td>(73.3)</td>
</tr>
<tr>
<td>Excluding Private Schools</td>
<td>189.4</td>
<td>106.8</td>
<td>121.2</td>
<td>91.4</td>
</tr>
<tr>
<td></td>
<td>(66.5)</td>
<td>(54.8)</td>
<td>(55.1)</td>
<td>(54.7)</td>
</tr>
</tbody>
</table>

Note: MPRTE and TT were estimated using techniques described in the text. Standard Errors in parenthesis. In the third row we estimate the parameters among those not attending private high schools in 2001 (we leave out 13,352 people).

Table 10: Semiparametric estimation for TT and MPRTE considering categories for Vocational Education

<table>
<thead>
<tr>
<th></th>
<th>TT</th>
<th>$Z^k_\alpha = Z^k + \alpha$</th>
<th>$P_\alpha = P + \alpha$</th>
<th>$P_\alpha = (1 + \alpha)P$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial</td>
<td>114.5</td>
<td>102.8</td>
<td>102.1</td>
<td>99.8</td>
</tr>
<tr>
<td></td>
<td>(59.9)</td>
<td>(48.9)</td>
<td>(49.3)</td>
<td>(48.4)</td>
</tr>
<tr>
<td>Industrial</td>
<td>42.9</td>
<td>31.3</td>
<td>30.6</td>
<td>28.2</td>
</tr>
<tr>
<td></td>
<td>(70.1)</td>
<td>(58.5)</td>
<td>(58.9)</td>
<td>(57.7)</td>
</tr>
<tr>
<td>Technical</td>
<td>236.9</td>
<td>225.2</td>
<td>224.5</td>
<td>222.2</td>
</tr>
<tr>
<td></td>
<td>(62.8)</td>
<td>(49.4)</td>
<td>(50.0)</td>
<td>(48.6)</td>
</tr>
<tr>
<td>Agricultural</td>
<td>161.4</td>
<td>149.8</td>
<td>149.1</td>
<td>146.8</td>
</tr>
<tr>
<td></td>
<td>(66.1)</td>
<td>(56.1)</td>
<td>(56.4)</td>
<td>(55.6)</td>
</tr>
<tr>
<td>Maritime</td>
<td>447.3</td>
<td>435.6</td>
<td>434.9</td>
<td>432.6</td>
</tr>
<tr>
<td></td>
<td>(137.1)</td>
<td>(133.0)</td>
<td>(133.3)</td>
<td>(132.8)</td>
</tr>
</tbody>
</table>

Note: MPRTE and TT were estimated using techniques described in the text.
Figure 1: Number of vocational schools among different municipalities in the north zone of Chile in 2000.

Notes: North zone corresponds to regions I to V in 2000. Black municipalities have between 4 and 15 vocational schools, dark grey municipalities have between 2 and 3 vocational schools, light gray municipalities have one vocational schools and the white municipalities have no vocational schools. Source: Ministry of Education database.
Figure 2: Percentage of non formal work in the period January 2010 and May 2011 between individuals not enrolled in tertiary education in 2010


Figure 3: Contract Type in percentage

Source: ETEL 2008, IADB.
Figure 4: Propensity Score support

Note: We use predicted values from table 6.
Figure 5: $MTE$ with 90 percent confidence interval. Vocational vs Comprehensive education.

Note: To estimate the function plotted here, we first use a polynomial in $P(Z)$ to approximate $K(p)$ in the outcome equation. Then we use a locally quadratic function in $P(Z)$ with a bandwidth of 0.22 to obtain the derivative of the outcome function with respect to $P(Z)$. The figure is generated evaluating the derivative of $E(Y|X = x, P(Z) = p)$ with respect to $p$ at the average value of $X$ and we replace all dummies for vocational education categories with zero. Ninety percent standard error bands are obtained using bootstrap (250 replications).
Figure 6: Weights for MPRTE.

Note: The scale of y-axis is the scale of the MTE. Weights are scaled to fit the picture.
Figure 7: MTE with 90 percent confidence interval. Vocational vs Comprehensive education, excluding individuals who attended private high schools.

Note: To estimate the function plotted here, we first use a polynomial on $P(Z)$ to approximate $K(p)$ in the outcome equation. Then we use a locally quadratic function of $P(Z)$ with a bandwidth of 0.22 to obtain the derivative of the outcome function with respect to $P(Z)$. The figure is generated evaluating the derivative of $E(Y|X = x, P(Z) = p)$ with respect to $p$ at the average value of $X$ and we replace all dummies for vocational education categories to zero. Ninety percent standard error bands are obtained using bootstrap (250 replications).
Figure 8: MTE with 90 percent confidence interval. Technical vocational education vs Comprehensive Education.

Note: To estimate the function plotted here, we first use a polynomial on $P(Z)$ to approximate $K(p)$ in the outcome equation. Then we use a locally quadratic function of $P(Z)$ with a bandwidth of 0.22 to obtain the derivative of the outcome function with respect to $P(Z)$. The figure is generated evaluating the derivative of $E(Y|X = x, P(Z) = p)$ with respect to $p$ at the average value of $X$ and we replace all dummies for vocational education categories to zero. Ninety percent standard error bands are obtained using bootstrap (250 replications).