AN ABSTRACT OF THE DISSERTATION OF

Rodrigo A. Echeverria for the degree of Doctor of Philosophy in Agricultural and Resource Economics presented on July 28, 2006.
Title: Essays on Productivity, Economic Geography and Trade: The Case of Chile.

Abstract approved: ___________________________________
Munisamy Gopinath

This dissertation investigates the relative importance of firm-specific and geographic characteristics for export behavior in the Chilean primary and processed food industries. The first essay develops a new method for measuring geographic characteristics to account for economic activity in adjacent, but separate spatial units. In the application to the Chilean manufacturing industry, the proposed index better identifies the presence of locational forces (e.g., technological spillovers or natural advantages) than do traditional indexes. Results suggest a higher geographic concentration of Chilean manufacturing firms through technological spillovers in highly populated areas, and access to natural resources in areas that are farther from large cities.

The second essay analyzes the determinants of Chilean farms' decision to produce exportables, i.e., export participation. An export behavior model is estimated using farm-level data from the Chilean Census of Agriculture and a two-stage conditional maximum likelihood procedure. Results show that a farm's efficiency or productivity is more important than its location for its export participation. When a high-productivity farm locates in a region with better geographic characteristics, its

likelihood of producing for export markets is higher. On the other hand, an opposite result is obtained when a low-productivity farm locates in regions with better geographic attributes. The latter suggests that farms must achieve a minimum level of efficiency for geographic characteristics to positively affect their export participation.

The third essay investigates firms' decision to export as well as that on how much to export (intensity) in the Chilean processed food industries. Results show the relative importance of sunk costs, foreign ownership and firm size in the Chilean firms' export decision. Productivity and geography play a more prominent role in firms' export-intensity decision in selected industries. In general, firm-specific characteristics appear to be more important than geographic attributes for export behavior.

The three essays contribute to a better understanding of firms' export behavior, in particular those in the Chilean agriculture and processed food industries. By providing insights into factors affecting export behavior, these three essays have implications for public policies to encourage firms' participation in global markets.

Essays on Productivity, Economic Geography and Trade:
The Case of Chile

by
Rodrigo A. Echeverria

A DISSERTATION

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Doctor of Philosophy

Presented July 28, 2006
Commencement June 2007

Doctor of Philosophy dissertation of Rodrigo A. Echeverria presented on July 28, 2006.

APPROVED:

Major Professor, representing Agricultural and Resource Economics

---

Head of the Department of Agricultural and Resource Economics

---

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to my reader upon request.

Rodrigo A. Echeverria, Author

ACKNOWLEDGEMENTS

I would like to express my special gratitude to my advisor, Dr. Munisamy Gopinath. Gopi guided me through all the years of my doctoral studies, listening and understanding me with an incredible patience. His support was crucial to success in my program. I will always be grateful for his important contribution to my academic development.

Also, I would like to thank to my committee members, Dr. Lori Cramer, Dr. Larry Lev, Dr. William Jaeger, and Dr. Jeff Reimer, whose comments helped me to improve the dissertation.

I must also thank Dr. Rolf Färe, who had a special interest in my work, and from whom I received valuable comments and help.

TABLE OF CONTENTS

TABLE OF CONTENTS (Continued)

TABLE OF CONTENTS (Continued)

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE

INTRODUCTION

The relationship between international trade and economic growth has often been explored in the context of aggregate economic units such as a country, industry or sector (Frankel and Romer, 1999; Giles and Williams, 2000; Easterly, 2004; Dollar and Kraay, 2004). However, recent studies have focused on microeconomic aspects of international trade, especially the export behavior of firms (Roberts and Tybout, 1997). Using manufacturing firm-level data, several studies have found that high-productivity firms self-select into export markets. Moreover, exporters are bigger, survive longer, have higher profitability, pay higher wages, and attract high skilled workers (Bernard and Jensen, 1995, 2004a). Most studies conclude that a firm's productivity is a key determinant of export behavior. Furthermore, such behavior results in a reallocation of resources within an industry or economy in favor of exporters leading to economic growth and development (Wagner, 2005; Melitz, 2003).

Simultaneously, the economic-geography literature, which focuses on the distribution of production factors within an economy, has shown that locational characteristics play an important role in firms' production and location decisions (Krugman, 1991a; Fujita, Krugman and Venables, 1999; Aitken, Hanson and Harrison, 1997). These studies find that economic activity including exports tends to be concentrated in certain regions relative to others, a phenomenon often termed geographic or spatial concentration. The sources of such concentration have been identified as locational spillovers (e.g. knowledge spillovers, lower transportation or transaction costs) and/or natural advantages (e.g. natural resources, climate). In other words, firms tend to concentrate in a location due to its geographic advantages (Krugman and Venables, 1995). For example, acquiring knowledge from neighbors can lower a firm's cost or help produce more innovative products, both of which can increase its global competitiveness.

Despite the relevance of geographic characteristics to firms' production decisions, few studies have considered such factors in their export behavior. Many of these studies control for geographic characteristics using categorical variables such as regional or provincial indicators (Roberts and Tybout, 1997; Bernard and Jensen, 2004a; Limao and Venables, 2001; Redding and Venables, 2003). This is surprising, especially when geographic concentration in conjunction with export activity appears to be related to spatial income inequality within many developing countries (Venables, 2005).

The objective of this dissertation is to investigate the relative importance of firm-specific and geographic characteristics in explaining firms' export behavior in the Chilean primary and processed food industries. To achieve this objective, three essays are presented. The objective of the first essay, *Geographic Concentration of the Chilean Manufacturing Industry*, is to extend measures of geographic concentration of economic activity for use in the analysis of Chilean firms' export behavior. The geographic distribution of economic activity appears to be more concentrated in developing than developed countries. For instance, the Santiago (Metropolitan) region of Chile accounts for 50% and 40% percent of national output and employment, respectively. Such a distribution could hinder the identification of geographic concentration with presently available indexes, especially when more disaggregated spatial units (e.g., counties) are analyzed. Moreover, these recent measures of geographic concentration do not consider economic activity in adjacent regions. The hypothesis is that measures of geographic concentration presently available may not be well suited for developing countries. An alternative measure of geographic concentration is proposed and applied to the case of Chile.

The second essay titled, *Productivity, Geography, and the Export Participation of Chilean Farms*, is a study of the relative effects of farm-specific and geographic characteristics on the export participation of Chilean farms. The focus is on export participation since farms, in general, do not export but participate in exportable production. Since agricultural production depends on geographic characteristics (natural advantages), the hypothesis here is that geographic characteristics have a stronger effect than farm-specific factors on farms' decision to participate in exportable production.

In the third essay, *Export Behavior in the Chilean Food Processing Industry: The Role of Productivity and Geography*, the export behavior of firms in the Chilean processed food industry is analyzed. Here, the relative importance of firm-specific and geographic characteristics in the decision to export, as well as how much to export (i.e., intensity) are investigated. In addition, the availability of time-series data allow for an exploration of the role of sunk (entry and/or exit) costs in the export decision. The second and third essays are closely related, but the former analyzes export participation, while the latter directly measures firms' export decision and also analyzes the export intensity.

Understanding the relative effect of firm-specific and geographic characteristics on firms' export behavior can provide insights into the determinants of regional or local development, particularly in the context of developing countries. Recall that exporters attract high-skilled labor, pay higher wages and survive longer, which together bring about sustained economic growth and development. The key determinants of export behavior can then be impacted by alternative policies. For example, a firm's productivity can be improved by encouraging its own research and development or providing better managerial or organizational knowledge, which can be achieved by tax or subsidy and public training policies, respectively. The scope of this study is limited to studying the relative contribution of such characteristics in encouraging export participation. Additional research is required to evaluate alternative policies and their welfare implications for agriculture, processed food industries and the overall Chilean economy.

CHAPTER TWO

GEOGRAPHIC CONCENTRATION OF THE CHILEAN MANUFACTURING INDUSTRY

2.1 Introduction

Geographic or locational characteristics have been identified as key determinants of production structure and trade (Venables and Limao, 2002; Fujita, Krugman and Venables, 1999; Krugman, 1998; Krugman, 1991a, 1991b). Much of industrial production and economic activity in developed economies is concentrated in and around metropolitan areas. For instance, Fujita and Mori (2005) identify that about 30% of France's GDP is sourced from the metropolitan area of Paris. Similarly, trade participation, especially export production appears highly concentrated in certain regions. For example, in the case of the United States, 29% of exports originate from two states, California and Texas (Coughlin and Pollard, 2001). The recent empirical trade literature on firm-level decision to export finds high correlation between geographic or locational characteristics and export activity (Bernard and Jensen, 1995, 2004a).

Attempts to explain the spatial concentration of economic activity, referred to as the new economic geography, attribute it to natural advantages and/or technical spillovers (Venables and Limao, 2002; Fujita, Krugman and Venables, 1999; Krugman, 1998; Krugman, 1991a, 1991b). Natural advantages arise from the presence of raw materials or local conditions suitable to industrial activity (e.g., closeness to ports, specific climate conditions, presence of roads). Technical spillovers occur when a firm in a location benefits from knowledge or networks created by the presence of many other firms in the same area (e.g., abundance of skilled workers, research and development).

Despite the theoretical advances in the field of new economic geography, measuring geographic concentration of economic activity has received limited attention. The seminal contribution here includes the novel locational model of Ellison and Glaeser, EG, (1994, 1997), which resulted in an empirical measure (index) that provides evidence of geographic concentration in excess of that which is due to industrial concentration. Maurel and Sédillot, MS, (1999) provided a theoretical basis for location choice in the form of a probabilistic model, which led to an alternative index of geographic concentration. The EG and MS indexes have been employed in a number of studies on geographic concentration in manufacturing industries of developed countries (Alonso-Villar, Chamorro-Rivas and Gonzalez-Cerderia, 2004; Deveroux, Griffith and Simpson, 2004; Braunerhjelm and Borgman, 2004). The measurement and understanding of geographic concentration within an economy has helped sharpen the focus on economic development from the national (macro) to a regional (micro) level.

Surprisingly, such advances, especially in the measurement of geographic concentration, have not been extended to the developing countries' context. The applicability of these measures to developing countries, which are characterized by a significantly uneven spatial distribution of economic activity, appears limited (Krugman, 1999). Aside from the application viewpoint, traditional geographic variables suffer from excessive spatial aggregation or lack of specificity to firms or industries of interest (Limao and Venables, 2001). For instance, these indexes do not capture geographic concentration when economic activity occurs in separate but, adjacent spatial units. Similarly, these indexes are derived for specific industries but do not compare locations or regions within an economy.

In this essay, we first extend the MS index to account for economic activity in adjacent, but separate spatial units. The new adjacency index also allows for a comparison of geographic concentration across spatial units. Then, the EG, MS and adjacency indexes of geographic concentration are applied to the case of Chile, a developing country unlike that in previous studies. The case of Chile is, indeed, interesting for studying geographic concentration, since it has been a relatively open economy but, with significant regional disparities. For example, the country is divided into thirteen regions, but the Metropolitan (Santiago) Region accounts for 2 percent of the area, 50 percent of the production and 40 percent of the population (Annual National Manufacturing Survey, Chile, 1997).

In the first section of this essay we briefly review recent contributions in new economic geography. Then, the EG and MS indexes are described. Based on these indexes, the new index that accounts for adjacency is introduced, and the location-specific geographic measurement is derived. Next, these indexes are used to analyze the geographic concentration of the Chilean manufacturing industry. Finally, the conclusions of the essay are presented.

2.2 The Spatial Concentration of Firms

Following the pioneering work of von Thünen in the early nineteenth century and Marshall in the last century, industrial concentration has been well documented by geographers. Although economists recognized the importance of geography in their discipline, their attempts have lagged that of geographers in explaining spatial concentration of economic activity (Fujita, Krugman, and Venables, 1999; Fujita and Thisse, 2002). It was not until the early 1990s, with the analytical work of Krugman (1991b) that economists had developed a formal framework to include geography, leading to the so called "new economic geography."

Based on the monopolistic competition models of Dixit and Stiglitz (1977) and Krugman (1980), Krugman (1991b) developed a framework to explain how firms concentrate in a particular location. In Krugman's (1991b) model there are two sectors, a perfectly competitive agricultural sector and a monopolistically competitive manufacturing sector. Labor is the only factor of production with farmers being immobile and workers mobile. When a firm moves to a region it creates competition in the labor and goods market, increasing wages and decreasing product prices. Higher wages and more local varieties attract more workers to the concerned region increasing local expenditures, and the higher profits attract new firms. With decreasing transaction costs the original symmetric equilibrium becomes unstable and a core-periphery pattern appears, with an industrialized core and an agricultural periphery.

Following Krugman, other researchers have proposed new models of economic geography. Venables (1996) proposed a model of three sectors: a perfectly competitive one and two -an upstream and a downstream- monopolistically competitive sectors. With intersectoral labor mobility and input-output linkages, if a firm moves to another country, there will be a reduction of costs for the remaining firms. This reduction of costs is due to more efficient scale production of upstream firms due to the increased market size and the reduced fixed costs of the downstream firms as intermediates become cheaper. Thus, the reduction in transaction costs leads to a core-periphery pattern (Krugman, 1991a). Similarly, Martin and Ottaviano (2001) model industry location choice where growth is endogenous. In their model higher growth rates of a region with concentration in innovative activity will lead to a higher demand for differentiated goods, which together attract for firms to a location. As a result, the location with innovative activity experiences spatial concentration, while the other location specializes in the traditional products.

Despite economic modeling of economic geographic concentration of firms, it was not until the seminal work of Ellison and Glaeser (1994, 1997) that empirical techniques differentiated between pure geographic forces and economic determinants. Ellison and Glaeser (1997) proposed a localization model where geographic concentration could be motivated by two agglomerative forces: natural advantage or spillovers controlling for industrial concentration. Locational spillovers can be physical spillovers (for example when the presence of a firm reduces the transportation costs attracting a second firm), or intellectual spillovers. Natural advantages refer to some specific characteristics of an area, such as access to natural resources, and closeness to markets. When these two forces are not present, firms choose locations like throwing darts on a scaled dartboard, that is, the location process is random, and concentration measures are the equivalent for spillovers and natural advantages. Using data from the US manufacturing industry they observed strong geographic concentration only in a few industries.

Along the lines of Ellison and Glaeser (1997), Maurel and Sedillot (1999) developed an index of concentration from a probabilistic model that differs from the EG index in the measurement of raw geographic concentration. Using data on the French manufacturing industry they found that extractive industries are highly geographically concentrated, mainly determined by natural advantages. High-tech industries also show a high geographic concentration but driven by knowledge spillovers.

Using the EG and MS indexes, a series of empirical studies have examined geographical concentration. Alonso-Villar, Chamorro-Rivas and Gonzalez-Cerderia (2004) in Spain found that there is concentration of high-tech industries and those linked to the provision of natural resources. In Uk, Deveroux, Griffith and Simpson (2004) found geographic concentration mostly in low-tech industries. Braunerhjelm and Borgman (2004) found that the Swedish industry is highly geographically concentrated, with the effect more pronounced for knowledge-intensive manufacturing industries and those that intensively use raw materials.

2.3 The Geographic Concentration Indexes

Although there are several indexes to measure spatial concentration of industrial activity, the EG and MS indexes have the advantage of differentiating between the geographic and the industrial components. In the EG model, there are N plants with shares $z_1 \dots z_N$ of a specific industry's employment in a country. Moreover, the country has M geographic areas with shares $x_1 \ldots x_M$ of total employment. We assume that the M geographic areas are independent and identically distributed random variables that can take values $1,\ldots,M$ with probabilities $p_1,\ldots p_M$. These probabilities can be thought of as the relative size of each area, so it is commonly assumed that $p_i = x_i$. The fraction of a particular industry locating in area i is:

(1) $$s_i = \sum_{j=1}^{N} z_j u_{ji}$$

where j represents plants and u_{ji} is a Bernoulli random variable that takes the value 1 if the plant j locates in area i, and 0 otherwise. If the process of location were completely random, the location process should lead to the same distribution of employment given by the aggregate. That is $P(u_{ji} = 1) = x_i$.

When two firms locate in the same area, Ellison and Glaeser (1997) suggest the existence of a correlation between the two decision, given by $\gamma = Corr(u_{ji}, u_{ki}),\ \ \gamma \in [-1,1],$ which describes the strength of locational attributes (spillovers or natural advantages). They define a normalized measure of raw geographic concentration of an industry, G_{EG}, by:

(2) $$G_{EG} = \frac{\sum_{i=1}^{M}(s_i - x_i)^2}{1 - \sum_{i=1}^{M} x_i^2}$$

For each area i $(i = 1, 2, ..., M),$ this index compares the fraction of employment of a specific industry (s_i) with the aggregate employment share (x_i). Then, Ellison and

Glaeser (1997) control for industrial concentration in deriving the final index of geographic concentration as follows:

(3) $$\hat{\gamma}_{EG} = \frac{G_{EG} - H}{1 - H}$$

where H is a Herfindahl index defined as $\sum_{j=1}^{J} z_j^2$.

Although the EG index is an unbiased estimator of γ, it does not have a theoretical basis. Hence, Maurel and Sedillot (1999) provided a probabilistic framework for the location choice and redefined the index of geographic concentration as:

(4) $$G_{MS} = \frac{\sum_{i=1}^{M} s_i^2 - \sum_{i=1}^{M} x_i^2}{1 - \sum_{i=1}^{M} x_i^2}$$

and

(5) $$\hat{\gamma}_{MS} = \frac{G_{MS} - H}{1 - H}$$

which is an unbiased estimator of γ.

The interpretation of the two indexes of geographic concentration $\hat{\gamma}_{EG}$ and $\hat{\gamma}_{MS}$ is similar. If G (raw or pure geographic concentration) is greater than H (industrial concentration), the index γ indicates that the industry is geographically or spatially concentrated. On the other hand, if $G < H$ then the industrial concentration is stronger than the geographical concentration. To illustrate further, suppose there are only ten plants in a country with a large number of areas (50). Clearly the Herfindahl index H will be high (close to 1), but if the index G is lower, then plants location decisions are not correlated.

2.4 Accounting for Adjacency

A characteristic of the EG and MS indexes is that they do not treat the geographic location of a plant as a particular point in a map, but rather as simple aggregated geographical areas, such as counties or provinces. In Duranton and Overman's (2005) words, "… *after aggregation has taken place, spatial units are treated symmetrically so that plants in neighboring spatial units are treated in exactly the same way as plants at opposite ends of a country*." A solution to this problem is to use distance-based methods developed in Marcon and Puech (2003) and Duranton and Overman (2005). However, there are several factors that encourage the continued use of MS and EG indexes. The first is that data on the specific location of a plant are either unavailable or considered confidential. In addition, it is reasonable to expect that plants will make the location decision in terms of closeness or proximity to a place with locational advantages. For example, a plant looking to locate near a big market would prefer an industrial suburb or a nearby, low-cost town. In this case, the location decision is not based on the exact measurement of distance in meters or feet but, in terms of how close the two regions of interest are to each other. Therefore, the aggregation of spatial units into regions and the indexes of geographic concentration should account for economic activity in adjacent or neighboring units. With this in mind, we propose an index of geographic concentration which accounts for economic activity in adjacent spatial units, solving the problem already described. The index is based on the probabilistic model of MS and its derivation is described in appendix 1.1. The index is defined as:

(6) $$\widehat{\gamma^A} = \frac{\widehat{G^A} - \sum_{i=1}^{M} s_i^2}{1 - \sum_{i=1}^{M} s_i^2} ,$$

with

(7) $$\widehat{G^A} = \frac{\sum_{r=1}^{R} m_r^2 - \sum_{r=1}^{R} {x_r^*}^2}{1 - \sum_{r=1}^{R} {x_r^*}^2} ,$$

where m_r is the fraction of industry employment located in the *r*-th normalized macro-unit, x_r^*, created by adjacent spatial units. Thus, a macro-unit could include several adjacent units, so it is possible to have several macro-units in a country for a particular industry. Equation (9) and (10) are analogous to the raw and final geographic concentration, G^{MS} and γ^{MS} respectively, of Maurel and Sédillot (1999). Note that $\sum_{i=1}^{M} s_i^2$ is the equivalent of $\sum_{j=1}^{N} z_j^2$ (the Herfindahl index) but, applies to aggregate plants in our case unlike that in the MS index. Hence, γ^A controls for industrial concentration of aggregate plants. Similarly, the G^A index measures the geographic concentration in excess of productive or capacity concentration in a macro-unit.

Note that if the N plants of an industry locate only in one region *i*, then there is no adjacency effect, and $\gamma^{MS} = 1$. However, if at least one plant locates in an adjacent area *h*, then there will be an adjacency effect, resulting in $\gamma^{MS} < 1$ and $\gamma^{A} = 1$. Now, if we assume that the smallest possible plant is located in the adjacent region *h*, then $\lim_{\sum_{i=1}^{M} s_i^2 \to 1} \gamma^{MS} = 1$ and $\gamma^{A} = 1$. Consequently, $\max(\gamma^{MS} + \gamma^{A}) = 2$. This leads us to propose the following general index of geographic concentration: [1]

$$(8) \qquad \gamma^{AE} = \begin{cases} \dfrac{\gamma^{MS} + \gamma^{A}}{2} & \textit{if there are adjacent spatial units} \\ \gamma^{MS} & \textit{if there is no adjacent spatial units, } \gamma^{A} \leq 0\textit{, or } \gamma^{A} < \gamma^{MS} \end{cases}.$$

Equation (8) shows that the macro-unit interaction reported by γ^{A} will be in addition to that reported by the MS index, γ^{MS}, resulting in a full concentration effect, γ^{AE}. So, as long as there is geographic concentration in adjacent spatial units, the γ^{AE} index will be higher than the γ^{MS} index. To avoid confusion, we will henceforth refer to γ^{AE} as the adjacency effect, AE, index.

2.5 A Ranking of Locations

The EG and MS indexes provide information on the degree of geographic concentration in each industry, but have not been used to compare locations or regions. For the latter, the common procedure is to look for the spatial units that have the highest employment share of a particular industry that has a relatively large Herfindahl index, H (Deveroux, Griffith and Simpson, 2004).

In this essay we propose a more concrete approach to compare the degree of geographic concentration across locations or regions. For this purpose, the employment share of each location, s_i, is multiplied by the geographic concentration index, γ_j, of each industry *j*. Thus, we generate a measure (index) of geographic concentration for each industry *j* at location *i*: $s_i\gamma_j$. This index captures the geographic attributes, i.e. natural advantages or technical spillovers, of a particular location and provides a ordering of locations according to their level of geographic concentration.

2.6 Data

The employment data used in this essay are from the Chilean Annual National Manufacturing Survey (ENIA) that covers the time period 1995 to 2003. This survey is compiled for plants with more than 20 employees. Plants are classified according to the four-digit International Standard Industrial Classification (ISIC) system at the regional, provincial and county level, but the exact street address of plants is not reported. Consistent with previous studies, only industries with more than one plant and industries that were present in all years are considered in our analysis. The sample has a total of 92 industries at the 4-digit level and the number of plants range between 4342 (2001) and 5342 (1996).

2.7 Geographic Concentration in the Chilean Manufacturing Sector

Table 2.1 shows the mean, median and standard deviation of the EG index (γ^{EG}), MS index (γ^{MS}), and the adjacency effect index (γ^{AE}) for the 92 four-digit Chilean manufacturing industries during 1995-2003 at three levels of spatial aggregation: region, province and county. Recall that these indexes range between -1 and 1 and positive values denote spatial concentration in excess of industrial concentration as in equations (3), (5) and (8).

In table 2.1, the MS index differs substantially from the EG index (and the adjacency effect index), with a difference between their means of more than 100% at the regional level, and 15% at the county level (table 2.1). The source of this difference is the way in which the indexes are calculated. In the EG index, the expression $\sum_{i=1}^{M}(s_i - x_i)^2$ that appears in the raw geographic concentration index, G_{EG} , is calculated for each location. Thus, G_{EG} will vary depending on the distribution of employment over spatial units. The EG index will expand when an industry with relatively large plants is located in an area with relative lower aggregate employment share, or it will contract when this industry is located in an area with a higher employment share (Allonso-Villar, Chamorro-Rivas and Gonzalez-Cerdiera, 2004). On the other hand, in the MS index, the expression $\left(\sum_{i=1}^{M} s_i^2 - \sum_{i=1}^{M} x_i^2\right)$ in the numerator of G_{MS} (equation 5) has higher values when large industries are located in areas with higher aggregate employment shares, and vice versa. The problem of the EG index is evident in the case of Chile, where the distribution of the employment is highly uneven (region 13, table 2.2).

The means and medians of γ^{MS} and γ^{AE} show a similar tendency through time at the three geographical levels, although the adjacency effect index is always greater, reflecting the concentration of economic activity located in adjacent spatial units (table 2.1). The means of these two indexes differ by 3% at the regional level, 12% at the province level, and 91% at the county level. These differences reflect the fact that most Chilean manufacturing activity is localized in few regions. Indeed, most of the economic activity is concentrated in one region (13) of the country, as shown in table 2.2. However, at the province and county levels, the AE index captures geographic concentration arising from adjacent economic activity, which explains its difference from the MS index.

Figure 2.1 presents the distribution of the indexes for the year 2003 for the 92 four-digit industries again at three levels: region, province and county.[2] For each of the three geographic divisions, the EG index clearly differs from the other two indexes. With a higher frequency around zero, the EG index identifies less spatial concentration than that observed with the other two indexes. This again reflects the problem of the EG index when big plants locate in the Metropolitan Region, as was previously noted. Besides, this expansion-contraction of the EG index does not necessarily bind γ^{EG} between -1 and 1. In panel (a) and (d) of figure 2.1, the EG index takes values greater than one for a few industries, contradicting the correlation concept underlying the location decisions of two plants. Although this difficulty of the EG makes the MS based-approach preferable, we include it in our discussion for comparison purposes.

Consistent with previous studies, the geographic concentration indexes change depending on the aggregation of the spatial units. The smaller the spatial unit, the lower the indexes. Thus, the regional level indexes show a higher spatial concentration than the province-level indexes, which are higher than those at the county level. Therefore, comparisons of geographic concentration indexes between countries should consider the size of the geographical divisions in explaining the differences. Figure 2.1(b), 2.1(c), 2.1(e) and 2.1(f) shows that the overall localization process of the Chilean manufacturing industries is not random at a region and province level, but rather there is a strong geographical concentration. At the county level, the indexes present a more skewed distribution around zero, showing a more random localization process, although the adjacency effect index shows relatively larger geographic concentration. It is interesting to note that the distribution of other countries' indexes is closer to the county-level distribution in this study (Maurel and Sedillot, 1999 – France; Deveroux, Griffith and Simpson, 2004 - UK). This suggests that the manufacturing industry of Chile exhibits spatial concentration at the regional and provincial level similar to those in other countries. This high geographic concentration is reinforced when analyzing the distribution of the Herfindahl index of the 92 four-digit industries for 2003 shown in figure 2.2. The distribution of this index is different from the Herfindahl indexes reported in countries like, USA (Ellison and Glaeser, 1997), France (Maurel and Sédillot, 1999), and UK (Deveroux, Griffith and Simpson, 2004). It seems that Chile has a higher proportion of big size manufacturing plants, which leads to higher Herfindahl index values.

2.8 Geographic Concentration by Industry

Tables 2.3 and 2.4 present spatial concentration by (four-digit) industries, in particular the 15 high- and low- concentration industries at the county level. These two tables include the number of plants, Herfindahl index (H), and the EG, MS and AE geographic concentration indexes. The values in parenthesis show the rank of the industries obtained by ordering the corresponding index.

Correlation coefficients between the ranks show a value of 0.77 between AE and MS, 0.75 between MS and EG, and 0.51 between the AE and EG indexes. As noted earlier, the low correlation between the AE and EG indexes is due to the AE index's derivation based on the MS index, and therefore we will not focus on the EG index. The differences between the AE and MS indexes correspond to adjacency effects, which are clearly observed in some industries (e.g. industries 1551, 2913, 2893 and 2696). To illustrate these differences, consider the industry 1551, "distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials" that in Chile corresponds mainly to the production of "Pisco," a liquor produced from grapes. This industry is localized in 5 counties, some of them adjacent to each other as shown in figure 2.3. This creates three macro-regions or pairs of adjacent counties: macro-regions 248_254, 250_254 and 605_623. The calculated MS index is 0.003, which indicates no evidence of locational advantage for this industry. However, from the map it is evident that plants are locating in a specific (macro) area. In this case, plants are locating close to the production of grapes with particular characteristics required to produce the liquor. This locational effect is captured by the adjacency index that is added to the county specific index of MS. The final index, $\gamma^{AE} = 0.266$, indicates a geographic concentration that better describes the observed locational distribution of plants. Similar localization patterns explain the large difference between the MS and AE indexes for certain other industries.

For comparison purposes, several studies grouped industries by their degree of localization (Ellison and Glaeser, 1997; Maurel and Sédillot, 1999; Devereux, Griffith and Simpson, 2004; Allonso-Villar, Chamorro-Rivas and Gonzalez-Cerdiera, 2004). Industries with index values less than 0.02 are considered as not Very Agglomerated, between 0.02 and 0.05 as Somewhat Agglomerated, and above 0.05 as Very Agglomerated. According to this categorzation, 59%, 57% and 31% of industries are not Very Agglomerated according to the MS, EG and AE indexes, respectively. On the other hand, there are 24%, 22% and 50% of Very-Agglomerated industries based on the MS, EG and AE indexes, respectively. The MS and EG indexes follow the same pattern that has been found in the US, UK and France. However, the AE index shows a very different pattern to those reported by the EG and MS indexes. The former provides more evidence of spatial concentration in Chilean manufacturing industries. We believe this effect can be attributed to accounting for adjacent spatial units with economic activity, which was considered to be a serious measurement issue by other authors who have analyzed geographic distribution of employment (Devereux, Griffith and Simpson, 2004, page 545, paragraph 3). Another way of interpreting the AE index is to consider a macro-unit as a spatial unit that extends beyond the political and administrative borders of the individual units that compose them. Thus, the index captures the "pure" geographical forces that attract plants, without the interference of administrative or other non-geographical divisions.

2.9 Sources of Geographical Concentration

According to Ellison and Glaeser (1997) and others, two main forces attract firms to the same location: technological spillovers and natural resources. The results in table 2.3 do not easily lend themselves for such a categorization. For example, industry 2412 (manufacture of fertilizers and nitrogen compounds), with the largest geographic concentration index, is an extractive industry that depends on raw materials. However, industry 3320 (manufacture of optical instruments and photographic equipment), with the third largest geographic concentration index, depends more on high-skilled labor and likely benefits from technological spillovers. Such differences are also found in the less localized industries shown in table 2.4.

Using the location-specific concentration index derived in an earlier section, table 2.5 shows the 25 most spatially concentrated counties for 2003 ordered by the AE index. This table also contains the values and ranks for the MS and EG indexes. Although the ordering is different between the indexes, there is a similar pattern. Among these 25 counties, the most concentrated counties are those that are located in the Santiago province (code 131), with the Santiago county being the most concentrated unit. However, there are counties that are highly concentrated but that are far away from Santiago, such as Puerto Montt, Maria Elena, La Serena, Concepción, Vicuna and Mejillones as shown in figure 2.4.[3]

When analyzing the geographic concentration of industries that are localized in these counties, an interesting pattern appears. Industries located in areas with high employment shares, such as Santiago and Concepción, are either labor intensive or high-skilled labor industries. Examples of these industries are manufacture of bearings, gears, gearing and driving elements (2913); manufacture of medical and surgical equipment, and orthopedic appliances (3311); manufacture of electric motors, generators and transformers (3110); manufacture of wearing apparel, except fur apparel (1810); publishing of books, brochures, musical books and other publications (2211); manufacture of malt liquors and malt (1553); manufacture of optical instruments and photographic equipment (3320); manufacture of electric motors, generators and transformers (3110). On the other hand, those industries that are located far away from Santiago or Concepción are mainly extracting industries, that is, their locational decisions are driven by access to natural resources or raw materials. For example, manufacture of cordage, rope, twine and netting (1723) and processing and preserving of fish and fish products (1512) in Puerto Montt; manufacture of fertilizers and nitrogen compounds (2412) in Maria Elena; distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials (1551) in La Serena and Vicuna (adjacent counties); and manufacture of basic iron and steel (2710) in Talcahuano.

An analysis of the entire set of counties shows a similar pattern (figure 2.4). It appears that industries that make their decision to locate in Santiago or Concepción benefit from locational spillovers, such as access to high-skilled labor or a larger labor market. On the other hand, industries locating in areas other than Santiago or

Concepción seem to be attracted by the natural resources of the concerned area, i.e., extractive industries.

2.10 Conclusions

In recent years, microeconomics studies, especially in the international trade field, have identified geographic characteristics as important determinants of firms' production, trade participation and export supply. However, several of these studies do not carefully measure geographic characteristics, often relying on categorical variables for locational attributes. This essay has proposed an alternative measure of geographic or spatial concentration of economic activity, for use in microeconomic studies of trade participation. The proposed alternative measure does not suffer from excessive spatial aggregation or lack of firm- or industry-specificity, unlike traditional measures of geographic characteristics.

Based on recent geographic concentration indexes of Ellison and Glaeser (1994, 1997) and Maurel and Sedillot (1999), a new index of geographic concentration is proposed and derived. The new index of geographic concentration accounts for concentration of economic activity in adjacent, but separate spatial units. This feature of the new index is significantly relevant for countries with an uneven distribution of the economic activity (e.g., developing countries). Moreover, the new index lends itself easily for a ranking of locations based on the degree of spatial or geographic concentration.

The three indexes of geographic concentration (Ellison and Glaeser, Maurel and Sedillot and the new Adjacency-Effect index) are applied to data from the Chilean manufacturing industry. For this purpose, plant-level data from 1995-2003 from Chilean Annual National Manufacturing Survey are used. The new Adjacency-Effect index captures geographic concentration even when the analysis is carried out at a disaggregated level (e.g., counties). The other two indexes reveal relatively lower geographic concentration when counties are the basic unit of analysis. The Chilean manufacturing industries show an interesting pattern of geographic concentration: firms that locate in Santiago or Concepción benefit from locational spillovers, such as access to high-skilled labor or a larger labor market; in other areas, firms seem to be attracted by the natural resources of the concerned area, i.e., extractive industries.

BIBLIOGRAPHY

Alonso-Villar O, J.M. Chamorro-Rivas, and X. Gonzalez-Cerdeira. 2004. "Agglomeration Economies in Manufacturing Industries: the Case of Spain". *Applied Economics* 36(18): 2103-2116.

Bernard, A.B. and J. B. Jensen. 1995. "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987." *Brookings Papers on Economic Activity, Microeconomics*. 1995: 67-119.

Bernard, A.B. and J. B. Jensen. 2004. "Why Some Firms Export." *Review of Economics and Statistics* 86(2): 561-569.

Braunerhjelm, P. and B. Borgman. 2004. "Geographical Concentration, Entrepreneurship and Regional Growth: Evidence from Regional Data in Sweden, 1975-99." *Regional Studies* 38 (8): 929-947.

Coughlin C. and P. Pollard. 2001. "Comparing Manufacturing Export Growth across States: What Accounts for the Differences? *Federal Reserve Bank of St. Louis*.

Devereux M., R. Griffith, and H. Simpson. 2004. "The Geographic Distribution of Production Activity in the U.K.". *Regional Science and Urban Economics* 34 (5): 533-564.

Dixit, A.K., and J.E. Stiglitz. 1977. "Monopolistic Competition and Optimum Product Diversity." *The American Economic Review* 67(3): 297-308.

Duranton, G. and H. Overman. 2005. "Testing for localization using micro-geographic data." *Review of Economic Studies* 72, 1077-1106.

Ellison G. and E. Glaeser. 1994. "Geographic Concentration in US Manufacturing Industries: A Dartboard Approach." Working Paper No 3840 NBER.

Ellison G. and E. Glaeser. 1997. "Geographic Concentration in US Manufacturing Industries: A Dartboard Approach." *Journal of Political Economy* 105(5): 889-927.

Fujita M., P. Krugman, and A. Venables. 1999. *The Spatial Economy. Cities, Regions and International Trade.* Cambridge: MIT Press.

Fujita M. and T. Mori. 2005. "Frontiers of the New Economic Geography." *Papers in Regional Science*. 84(3): 377-405.

Fujita M. and J. Thisse. 2002. *Economics of Agglomeration: Cities, Industrial Location and Regional Growth.* Cambridge: Cambridge University Press.

Fujita M. and J. Thisse. 2003. “Does Geographical Agglomeration Foster Economic Growth? And Who Gains and Loses from It?.” *The Japanese Economic Review* 54(2): 121-145.

Hanson, G.H. 2000. “Scale Economies and the Geographic Concentration of Industry.” NBER Working Paper No. 8013, Cambridge, MA.

Krugman, P. 1980. “Scale Economies, Product Differentiation, and the Pattern of Trade.” *The American Economic Review* 70(5): 950-959.

Krugman, P. 1991a. Geography and Trade, MIT Press, Cambridge, MA.

Krugman, P. 1991b. “Increasing Returns and Economic Geography”. *Journal of Political Economy* 99(3): 483:499.

Krugman, P. 1998. “Space: The Final Frontier”. *Journal of Economics Perspectives* 12(2): 161:174.

Krugman, P. 1999. “The Role of Geography in Development”. *International Regional Science Review* 22(2): 142:161.

Limao, N. and A.J. Venables. 2001. “Infrastructure, Geographical Disadvantage and Transport Costs.” *World Bank Economic Review* 15(3): 451-479.

Martin, P. and G. Ottaviano. 2001. “Growth and Agglomeration.” *International Economic Review* 42(4): 947-968.

Marcon, E. and F. Puech, 2003. Evaluating the geographic concentration of industries using distance-based methods. Journal of Economic Geography 3, 409-428.

Maurel, F. and B. Sedillot. 1999. “A Measure of the Geographical Concentration in French Manufacturing Industries.” *Regional Science and Urban Economics* 29: 575-604.

Venables, Anthony. 1996. “Equilibrium Locations of Vertically Linked Industries.” *International Economic Review* 37(2): 341-359.

Venables, A. and N. Limao. 2002. “Geographical Disadvantage: A Heckscher-Ohlin-von Thunen model of International Specialization”. Journal of International Economics 58(2): 239-263.

Table 2.1. Geographic Concentration Indexes Statistics

	Ellison and Glaeser			Maurel and Sedillot			Adjacency Effect		
Year	Mean	Median	S.D.	Mean	Median	S.D.	Mean	Median	S.D.
				Regional Level					
1995	0.125	0.056	0.505	0.252	0.168	0.451	0.266	0.195	0.448
1996	0.123	0.049	0.455	0.268	0.220	0.442	0.278	0.237	0.442
1997	0.155	0.087	0.511	0.269	0.232	0.454	0.280	0.265	0.450
1998	0.138	0.077	0.464	0.289	0.221	0.446	0.299	0.234	0.444
1999	0.083	0.071	0.678	0.318	0.297	0.435	0.321	0.297	0.437
2000	0.174	0.118	0.354	0.357	0.378	0.446	0.364	0.378	0.443
2001	0.160	0.086	0.363	0.305	0.248	0.409	0.319	0.289	0.409
2002	0.172	0.108	0.347	0.322	0.229	0.408	0.333	0.236	0.408
2003	0.203	0.105	0.420	0.318	0.212	0.430	0.324	0.277	0.431
Total	0.148	0.082	0.465	0.300	0.238	0.435	0.309	0.270	0.434
				Province Level					
1995	0.098	0.038	0.382	0.194	0.152	0.407	0.231	0.179	0.377
1996	0.095	0.036	0.340	0.218	0.179	0.411	0.243	0.161	0.386
1997	0.102	0.056	0.379	0.205	0.140	0.397	0.231	0.158	0.378
1998	0.088	0.054	0.351	0.215	0.112	0.387	0.242	0.125	0.367
1999	0.045	0.067	0.560	0.237	0.119	0.399	0.266	0.164	0.378
2000	0.131	0.090	0.262	0.282	0.215	0.410	0.303	0.227	0.393
2001	0.121	0.089	0.231	0.224	0.116	0.359	0.254	0.181	0.341
2002	0.124	0.075	0.231	0.237	0.135	0.360	0.261	0.163	0.343
2003	0.158	0.094	0.269	0.224	0.108	0.361	0.258	0.171	0.341
Total	0.107	0.070	0.348	0.226	0.141	0.387	0.254	0.171	0.367
				County Level					
1995	0.020	0.006	0.064	0.026	0.001	0.082	0.074	0.042	0.124
1996	0.030	0.006	0.092	0.039	0.004	0.128	0.084	0.048	0.146
1997	0.035	0.007	0.110	0.044	0.004	0.140	0.087	0.055	0.149
1998	0.050	0.015	0.135	0.057	0.014	0.156	0.102	0.063	0.168
1999	0.044	0.015	0.116	0.053	0.010	0.149	0.099	0.066	0.166
2000	0.052	0.017	0.111	0.060	0.021	0.122	0.102	0.066	0.142
2001	0.047	0.015	0.121	0.049	0.014	0.131	0.084	0.047	0.147
2002	0.047	0.017	0.107	0.050	0.017	0.117	0.091	0.053	0.135
2003	0.047	0.014	0.122	0.051	0.013	0.125	0.089	0.043	0.145
Total	0.041	0.014	0.110	0.047	0.010	0.129	0.090	0.053	0.147

Table 2.2. Number of Spatial Units and Employment Share

Region	**Number of Provinces**	**Number of Counties**	**Employment Share**
1	3	10	2.1
2	3	9	4.0
3	3	9	1.1
4	3	15	1.5
5	7	38	5.7
6	3	33	4.0
7	4	30	4.3
8	4	52	14.1
9	2	31	2.3
10	5	42	8.0
11	4	10	0.5
12	4	11	0.8
13	6	52	51.6
Total	51	342	100.0

Table 2.3. Fifteen High-Concentration Industries and their Rank, at County Level

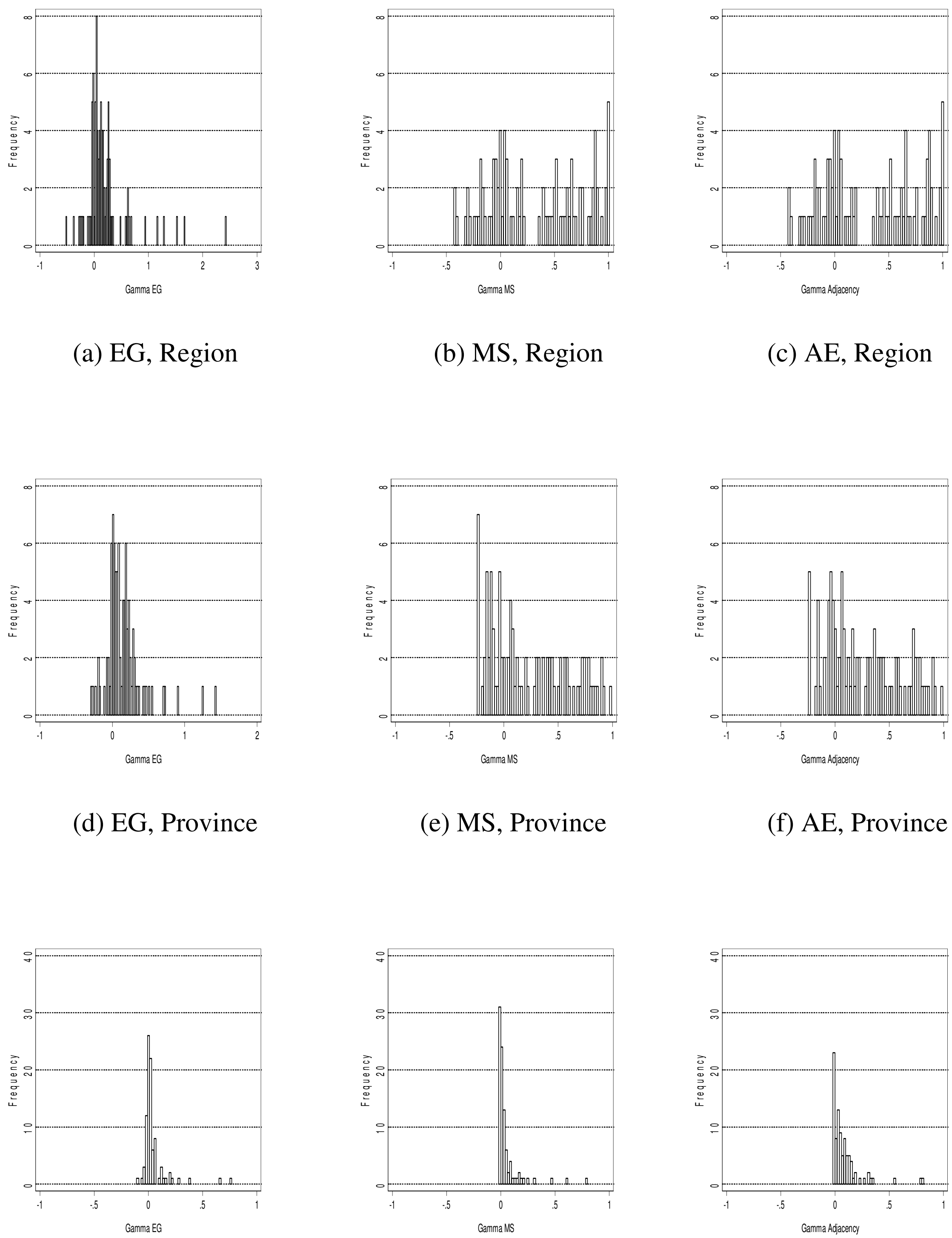
ISIC	Name	Plants	H	AE	MS	EG
2412	Manufacture of fertilizers and nitrogen compounds	3	0.473	0.808 (1)	0.616 (2)	0.671 (2)
1723	Manufacture of cordage, rope, twine and netting	6	0.241	0.790 (2)	0.790 (1)	0.768 (1)
3320	Manufacture of optical instruments and photographic equipment	5	0.331	0.560 (3)	0.481 (3)	0.377 (3)
3311	Manufacture of medical and surgical equipment and orthopedic appliances	10	0.144	0.360 (4)	0.175 (8)	0.129 (11)
2211	Publishing of books, brochures, musical books and other publications	59	0.043	0.330 (5)	0.248 (5)	0.199 (7)
1810	Manufacture of wearing apparel, except fur apparel	263	0.040	0.318 (6)	0.169 (9)	0.130 (10)
1553	Manufacture of malt liquors and malt	6	0.275	0.312 (7)	0.312 (4)	0.278 (4)
1551	Distilling, rectifying and blending of spirits; ethyl alcohol production from fermented materials	8	0.342	0.266 (8)	0.003 (58)	0.042 (25)
2913	Manufacture of bearings, gears, gearing and driving elements	9	0.148	0.237 (9)	0.040 (25)	0.026 (34)
3110	Manufacture of electric motors, generators and transformers	9	0.243	0.204 (10)	0.204 (6)	0.214 (5)
3592	Manufacture of bicycles and invalid carriages	7	0.313	0.200 (11)	0.200 (7)	0.210 (6)
2893	Manufacture of cutlery, hand tools and general hardware	7	0.396	0.189 (12)	-0.004 (67)	-0.108 (92)
2696	Cutting, shaping and finishing of stone	6	0.221	0.172 (13)	-0.019 (91)	-0.025 (87)
2892	Treatment and coating of metals; general mechanical engineering on a fee or contract basis	11	0.195	0.158 (14)	0.158 (10)	0.132 (9)
3694	Manufacture of games and toys	10	0.128	0.158 (15)	0.016 (42)	-0.010 (77)

Table 2.4. Fifteen Low-Concentration Industries and their Rank, at County Level

ISIC	Name	Plants	H	AE	MS	EG
3420	Manufacture of bodies (coachwork) for motor vehicles	28	0.141	-0.010 (78)	-0.010 (74)	-0.013 (78)
2029	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	20	0.235	-0.010 (79)	-0.010 (75)	0.004 (63)
2694	Manufacture of cement, lime and plaster	11	0.198	-0.013 (80)	-0.013 (77)	0.012 (51)
1554	Manufacture of soft drinks; production of mineral waters	37	0.079	-0.013 (81)	-0.013 (78)	-0.009 (76)
1533	Manufacture of prepared animal feeds	26	0.146	-0.015 (82)	-0.015 (79)	0.002 (66)
2320	Manufacture of refined petroleum products	9	0.331	-0.017 (83)	-0.017 (81)	-0.030 (88)
2212	Publishing of newspapers, journals and periodicals	24	0.214	-0.018 (84)	-0.018 (83)	-0.003 (71)
2922	Manufacture of machine-tools	11	0.400	-0.018 (85)	-0.018 (84)	0.002 (67)
2511	Manufacture of rubber tires and tubes; retreating and rebuilding of rubber tires	18	0.217	-0.019 (86)	-0.019 (85)	-0.014 (79)
3210	Manufacture of electronic valves and tubes and other electronic components	2	0.516	-0.019 (87)	-0.019 (86)	-0.019 (83)
2421	Manufacture of pesticides and other agro-chemical products	2	0.509	-0.019 (88)	-0.019 (87)	-0.021 (85)
3410	Manufacture of motor vehicles	4	0.528	-0.019 (89)	-0.019 (88)	0.014 (46)
1542	Manufacture of sugar	5	0.220	-0.019 (90)	-0.019 (89)	0.015 (45)
3312	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes	6	0.475	-0.019 (91)	-0.019 (90)	-0.006 (75)
1600	Manufacture of tobacco products	3	0.563	-0.019 (92)	-0.019 (92)	0.054 (21)

Table 2.5. The 25 High-Concentration Counties

Region	Province	County	County Name	AE	MS	EG
13	131	605	Santiago	1.34 (1)	0.75 (1)	0.50 (3)
10	103	535	Puerto Montt	0.75 (2)	0.74 (2)	0.72 (1)
2	21	221	María Elena	0.72 (3)	0.55 (3)	0.60 (2)
13	131	636	Quilicura	0.43 (4)	0.28 (4)	0.21 (4)
13	131	623	San Miguel	0.32 (5)	0.10 (11)	0.05 (17)
13	131	628	Estación Central	0.32 (6)	0.17 (7)	0.15 (6)
13	131	635	Renca	0.29 (7)	0.19 (5)	0.19 (5)
13	131	631	Quinta Normal	0.28 (8)	0.09 (13)	0.06 (15)
13	131	616	Macul	0.28 (9)	0.14 (8)	0.11 (7)
13	131	629	Cerrillos	0.27 (10)	0.09 (14)	0.07 (13)
13	134	650	San Bernardo	0.23 (11)	0.14 (9)	0.03 (29)
8	83	456	Talcahuano	0.20 (12)	0.19 (6)	0.09 (8)
13	131	610	Providencia	0.19 (13)	0.12 (10)	0.09 (9)
13	131	619	San Joaquin	0.17 (14)	0.06 (17)	0.05 (19)
13	131	609	Recoleta	0.16 (15)	0.06 (16)	0.04 (26)
13	131	630	Maipú	0.16 (16)	0.04 (27)	0.01 (41)
5	55	311	Viña del Mar	0.12 (17)	0.09 (12)	0.09 (10)
4	41	250	La Serena	0.12 (18)	0.00 (88)	0.02 (36)
13	131	608	Huechuraba	0.11 (19)	0.00 (55)	0.00 (337)
8	83	455	Concepción	0.10 (20)	0.06 (18)	0.05 (20)
4	41	254	Vicuña	0.10 (21)	0.00 (91)	0.02 (39)
13	131	606	Independencia	0.10 (22)	0.04 (25)	0.03 (32)
13	131	614	Ñuñoa	0.10 (23)	0.04 (28)	0.03 (30)
2	23	231	Mejillones	0.09 (24)	0.07 (15)	0.08 (12)
13	132	641	Lampa	0.07 (25)	0.01 (38)	0.02 (40)



(a) EG, Region (b) MS, Region (c) AE, Region

(d) EG, Province (e) MS, Province (f) AE, Province

(g) EG, County (h) MS, County (i) AE, County

Figure 2.1: Distribution of EG, MS and F indexes for the year 2003

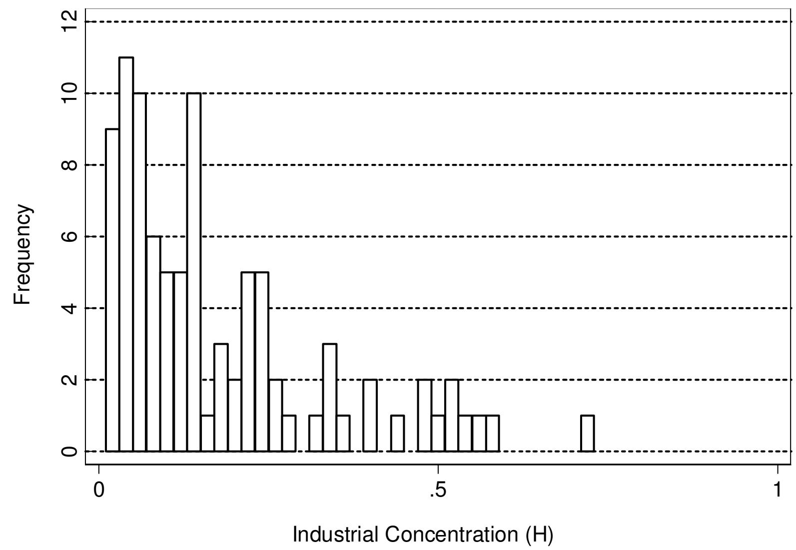


Figure 2.2: Distribution of Industrial Concentration Index for the year 2003

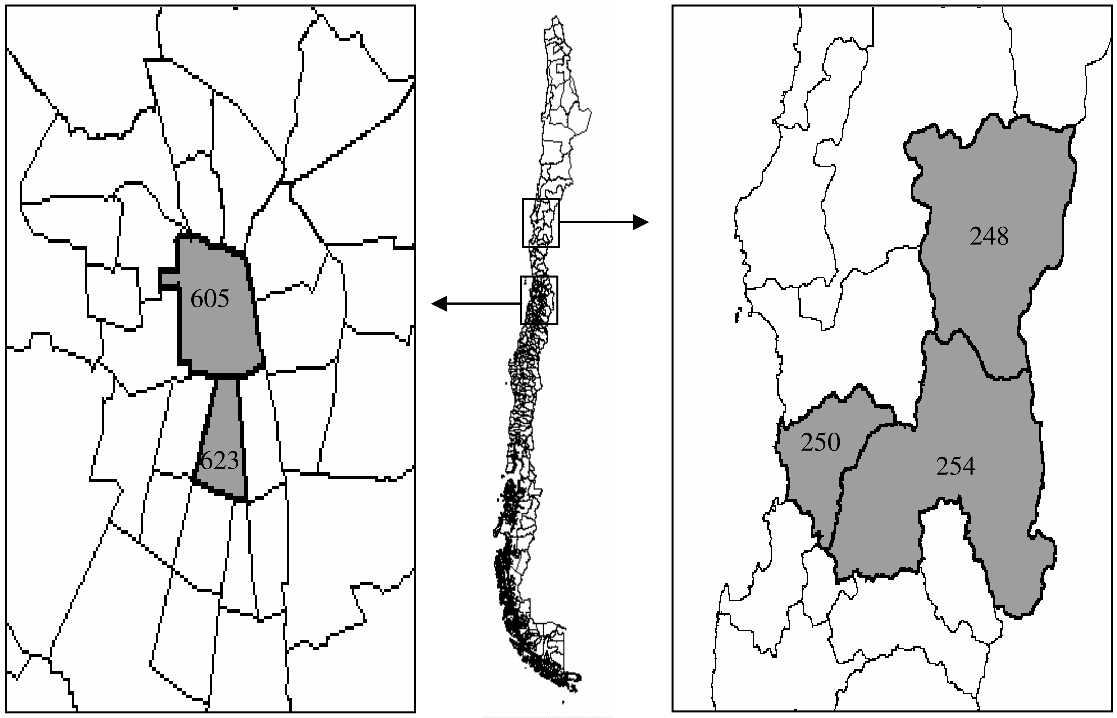
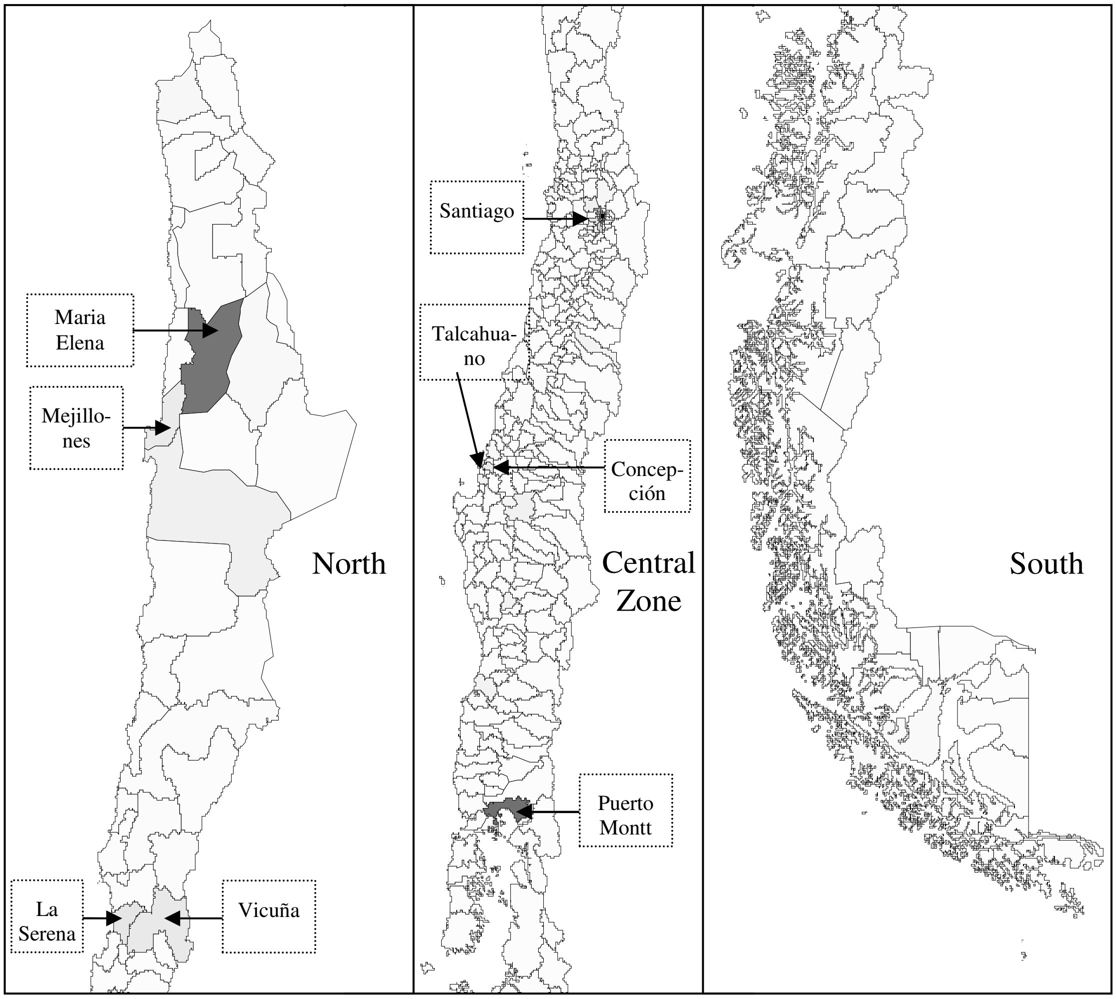


Figure 2.3: Macro-Regions of Chilean Industry 1551 Based on the Adjacency Index



*Darkness areas represent more geographic concentrated locations.

Figure 2.4: Chilean Map with Geographic Concentration by Location (County Level).

APPENDIX

Appendix 2.1: Derivation of the Adjacency Index

Following EG and MS indexes, let $z_1 \ldots z_N$ be plant shares in industry employment, where N is the number of plants in each industry, and $x_1 \ldots x_M$ be regional shares of of total employment, where M is the number of regions (or provinces or counties) in a country. Assume that two geographic units, i and h, are located adjacent each other, i.e., share a boundary. The union of these two regions creates a macro-geographic unit or macro-region r, whose share of total employment is given by:

(11) $$x_r = x_i + x_h,$$

where x_i and x_h are the shares of total employment of region *i* and *h* respectively. Let there be *R* pairs of individual regions into macro-units. Note that $\sum_{r=1}^{R} x_r$ is not necessarily equal to $\sum_{i=1}^{M} x_i$ but, the former must sum to one in the aggregate. Therefore, a normalization of the *r*-th macro-unit's share is required:

(12) $$x_r^* = \frac{x_r}{\sum_{r=1}^{R} x_r}.$$

Plants of a particular industry located in the same region *i* form an aggregate plant, j^*, which benefit from locational advantages. The aggregate plant's share of industy employment is then:

(13) $$s_{j^* \in r} = \sum_{j \in i,\ i \in r} z_j ,$$

where z_j is the share of the *j*-th plant in industry employment. Similarly, another plant or an aggregate plant, k^*, can be attracted by locational advantages of region *h* adjacent to the *i*-th region. Now, assume that plants are indifferent to locating in adjacent regions *i* or *h*, since they can gain the same benefit from locating in either region. Alternatively, the macro-unit can be considered as a location with same locational advantages of spatial unit *i* and *h*. In this case, the fraction of industry employment located in the *r*-th macro-unit is:

(14) $$m_r = (s_{j^* \in r} \cdot u_{j^* r})(s_{k^* \in r} \cdot u_{k^* r}) \quad ,$$

where $u_{j^* r}$ and $u_{k^* r}$ are Bernoulli variables that can take the value of 1 if j^* or k^* are located in the *r*-th macro-unit, and 0 otherwise. Note that m_r will be positive only if both Bernoulli variables take value 1, when both aggregate plants locate in the *r*-th macro-unit. If the process of location is completely random, it should lead to the same distribution of employment in the aggregate, i.e., $P(u_{j^* r} = 1) = x_r^*$ or $P(u_{k^* r} = 1) = x_r^*$. Following Ellison and Glaeser (1997) and Maurel and Sédillot (1999), the strength of locational advantages of macro-unit *r* when two aggregate plants, j^* and k^*, locate in it is:

(15) $$Corr(u_{j^* r}, u_{k^* r}) = \gamma^A \quad for \;\; j^* \neq k^* \quad ,$$

where γ^A represents the interaction of the location decision of both aggregate plants. Therefore, the probability that two (aggregate) plants locate in the same macro-unit is:

(16) $$P(r,r) = \gamma^A x_r^* (1 - x_r^*) + (x_r^*)^2 \quad .$$

Then, the probability that pairs of aggregate plants locate in the same macro-unit is:[4]

(17)
$$p^A = \sum_{r=1}^{R} P(r,r)$$
$$= \gamma^A (1 - \sum_{r=1}^{R} x_r^{*2}) + \sum_{r=1}^{R} x_r^{*2} \quad .$$

An unbiased estimator of p^A, along the lines of Maurel and Sédillot (1999), can be derived as:

(18)
$$\widehat{p^A} = \sum_r \frac{\sum_{\substack{i,h \in r \\ i \neq h}} s_i s_h}{\sum_{\substack{i,h \\ i \neq h}} s_i s_h} = \frac{\sum_{r=1}^{R} m_r^2 - \sum_{i=1}^{M} s_i^2}{1 - \sum_{i=1}^{M} s_i^2} \quad ,$$

where $s_i = s_{j^* \in i,\ i \in r}$ and $\sum_{r=1}^{R} m_r^2 = \sum_r \sum_{i,h \in r} s_i s_h$.

Replacing $\widehat{p^A}$ in equation (7) gives:

(19)
$$\widehat{\gamma^A} = \frac{\widehat{G^A} - \sum_{i=1}^{M} s_i^2}{1 - \sum_{i=1}^{M} s_i^2} \quad ,$$

where

(20)
$$\widehat{G^A} = \frac{\sum_{r=1}^{R} m_r^2 - \sum_{r=1}^{R} x_r^{*2}}{1 - \sum_{r=1}^{R} x_r^{*2}} \quad .$$

ENDNOTES

[1]The adjacency effect must identify geographic concentration that is not captured by the MS index. Therefore, there is no valid interpretation for values of γ^A that are negative or that reduce the concentration provided by the MS index.

[2]We arbitrarily choose year 2003 because it is the last year available, following other studies that have used the same criterion (Allonso-Villar, Chamorro-Rivas and Gonzalez-Cerdiera, 2004; Devereux, Griffith and Simpson, 2004).

[3]Although Viña del Mar is not in the Metropolitan Region, it is adjacent to it.

[4]Note that this aggregation considers adjacent areas forming one or more bigger macro-units.

CHAPTER THREE

PRODUCTIVITY, GEOGRAPHY, AND THE EXPORT PARTICIPATION OF CHILEAN FARMS

3.1 Introduction

Why do some farms decide to produce exportables while others produce domestic-market oriented commodities? In the context of manufacturing industries, firms' decision to produce for foreign markets and export, popularly termed the export decision, has been extensively addressed beginning with the contribution of Bernard and Jensen (1995). The emerging theoretical and empirical literature on factors that underlie a firm's decision to export, continue to export or exit a foreign market have improved our understanding of exporting firms' characteristics (Aw and Hwang, 1995; Aitken, Hanson and Harrison, 1997; Bernard and Jensen, 1997, 1999, 2004a; Roberts and Tybout, 1997; Bernard et al., 2003; Helpman, Melitz and Yeaple, 2004). The accumulated evidence indicates high-productivity firms self-select into export markets and exporters survive longer and pay higher wages relative to nonexporters in developed and developing economies (Richardson and Rindal, 1995; Wagner, 2005). Within an industry, resource reallocation in favor of fast-growing exporters is an important determinant of the observed correlation between exports and economic growth (Melitz, 2003; Bernard and Jensen, 2004b). However, the evidence as of now on whether exporting improves productivity, i.e., learning-by-exporting, remains mixed.

The export behavior modeled in the context of manufacturing sector does not apply directly to the case of primary agriculture, where farms often do not export and marketing firms make the export decision. However, farms decide on producing goods where the export intensity, i.e., share of exports in domestic production is either larger or smaller (Bernard and Jensen, 1995; Pavncik, 2002). Why is the decision to participate in exportable production important in the agricultural sector? Because, agriculture is one of the highly protected segments of developed and developing economies, and attempts to bring about successful liberalization of the agricultural sector have often been countered with structural-adjustment concerns (Aksoy and Beghin, 2005). Most studies of agricultural trade liberalization claim long-run benefits to reform, but cite significant structural adjustment and the short- to medium-term harm to farm and rural communities. These studies do not necessarily model firm- or farm-level decision making, which is a significant factor in the structural adjustment process from a protected regime to a market-based economy. Understanding farms' export participation would aid in creating successful exporters, and making liberalized and open-market policies politically feasible. As noted earlier, successful exporters bring about stable income growth to the specific industry and the broader economy.

The objective of this essay is to analyze the export participation of Chilean farms and to identify the relative importance of farm-specific and geographic characteristics in this decision. Indeed, Chile is an excellent example of the export-led growth theory with relatively open markets including the agricultural sector. Through unilateral liberalization in 1970s and 1980s, and bilateral agreements of 1990s, Chile has experienced relatively higher GDP and per capita income growth rates. Moreover, poverty has been reduced from 40 to 17 percent of the population during the same period (Agosin, 1999; Giles and Williams, 2000; World Bank, 2001). Analyzing Chilean farms' export participation will not only help understand regional income disparity but also provide insights into factors encouraging the successful transformation of protected regimes into open, market-based agricultural economies elsewhere (Avendaño, 2001).

In this essay, we set up an export behavior model along the lines of Aitken, Hanson and Harrison (1997). To apply this model, data on 8,284 Chilean farms are assembled for 1997 and an export participation rule similar to that of Pavcnik (2002) is utilized. The farm-specific characteristics in our analysis include efficiency (productivity), size and ownership structure. We also include a terms of trade measure between exportables and domestic-market oriented commodities in the export behavior model. In farms' export participation, we consider the role of geographic characteristics, which is consistent with the export decision and the economic geography literature (Krugman, 1991; Limao and Venables, 2001; Redding and Venables, 2003). We consider alternative representations of geographic characteristics: a measure of spatial concentration of economic activity, export intensities at county and regional levels, and individual measures of infrastructure, natural advantages, human capital, and institutional quality at the regional level. Since the export decision literature has addressed simultaneous determination of export decision and firm characteristics, we test and correct for possible endogeneity of regressors using a two-stage conditional maximum likelihood procedure.

The next section briefly outlines a theoretical basis for the export behavior, followed by a description of Chilean data including farm-specific and geographic factors. Section 3.4 presents the estimation procedure along with the tests and correction for endogenous regressors. The discussion of results is followed by a summary and conclusions.

3.2 An Export Behavior Model

Our approach to modeling export participation of Chilean farms is similar to that of Aitken, Hanson and Harrison's (1997) framework. Suppose firms (farms) choose to produce for the domestic market or the foreign market or both. Our framework can easily be extended to a case with more than one foreign market but, for simplicity, we aggregate all export destinations into a single foreign market. Assume that firms incur additional costs to produce for different markets, which are broadly termed as distribution costs. Furthermore, distribution costs in the domestic market are different from that of the foreign market. Total cost for a firm, indexed by *j*, is:

$$h^j(q_d^j + q_f^j) + m_d^j(q_d^j) + m_f^j(q_f^j)\,, \tag{1}$$

where d and f index domestic and foreign market, $h()$ and $m_i()$, $i = d, f$, are the production and distribution cost functions, respectively. Separability in production and distribution costs is assumed, and $h()$ and $m_i()$ are increasing and convex in their respective arguments.

The production decision of the *j*-th firm is given by the solution to:

(2) $$\max_{q_d, q_f}\{P_d q_d^j + P_f q_f^j - h^j(q_d^j + q_f^j) - m_d^j(q_d^j) - m_f^j(q_f^j)\}$$
$$s.t. \quad q_d, q_f \geq 0$$

where P_d and P_f are prices (not necessarily specific to the firm) received in domestic and foreign market, respectively.[1] The optimal output choice may be zero in either market. All firms produce positive quantities for the domestic market but, in practice, some firms produce zero exports. As in Aitken, Hanson and Harrison (1997), we only consider the possibility of a corner solution for the variable q_f^j. Let $q_f^{j^*}$ be the latent variable such that,

(3) $$\begin{cases} q_f^{j^*} = q_f^j & \text{if} \quad q_f^j > 0 \\ q_f^{j^*} = 0 & \text{otherwise.} \end{cases}$$

Given specific functional forms for *h()* and $m_i()$, Aitken, Hanson and Harrison (1997) derive the first-order conditions and specific solutions for $q_d^{j^*}$ and $q_f^{j^*}$. Given our interest in the firm export decision, we choose to focus on the estimation of the probability that a firm exports. Let the dummy variable y_j be:

(4) $$\begin{cases} y_j = 1 & \text{if} \quad q_f^j > 0 \\ y_j = 0 & \text{otherwise,} \end{cases}$$

which indicates whether or not a firm has positive exports. The estimation of the discrete choice model in equation (4) allows us to obtain consistent estimates of the underlying solution to $q_f^{j^*}$. It follows from equation (4) that the probability that the *j*-th firm exports is given by:

(5) $$\Pr(y_j = 1) = \Pr(\alpha + \beta X_j + \delta T_j^k + \gamma Z_j^k + \varepsilon_j > 0),$$

where ε_j is normally distributed, which permits the estimation of equation (5) as a binary probit model. In equation (5), X_j is a vector of firm-characteristics including size and productivity arising from the production and distribution cost functions, and β is the associated parameter vector of interest; T_j^k is the terms of trade between exportables and domestic production (P_f / P_d) with its corresponding parameter δ; Z_j^k is the *k*-th regional or geographic characteristics within which the firm operates originating either from the output prices or cost functions or both, and the parameter vector γ measures their relative importance to the probability of export production. Examples of Z_j^k include infrastructure, natural advantages, human capital, and institutional quality at the regional level. In the next section, we define both firm-specific and geographic characteristics, followed by a discussion of related estimation issues. The latter emphasizes the possible endogeneity of regressors, its testing and corrections for associated biases in estimated parameters.

3.3 Chilean Data

Identifying exporters in agriculture is a challenge since farms generally do not directly export. In this study, we focus instead on export participation, i.e., the decision to produce exportables. In the following, we outline a strategy to identify farms that are willing and able to participate in exportable production. We recognize that our rule will uniquely identify farms' export participation, but the resulting list of exportables may vary by country.

Data from the Chilean Agricultural Planning Office (ODEPA) show that fruits and fruit-derivatives (e.g., wine) accounted for about 80 percent of Chilean agricultural exports during 1990-2000 (ODEPA, 2001). Around 50% of total fruit production was exported, and 15 fruits accounted for 93 percent of all fruit exports. The second largest export group is vegetables and flowers accounting for another 11 percent of exports, while traditional agricultural commodities like grains and animal products (e.g., beef) constituted a small share (< 6 percent) of exports. Based on this data, we identify a set of twelve crops that are considered traditional and not exportable. Consequently, farms market participation or orientation is defined according to what they produce:

- Exporter ($q_f^{j^*} > 0$): Farms producing for the export market, if they only produce some or all of the (15) exportable fruits
- Traditional ($q_d^{j^*} > 0,\ q_f^{j^*} = 0$): Farms producing for the domestic market, if they only produce some or all of the (12) non-exportable traditional crops

Note that the above categorization is not unlike that of Pavcnik (2002), who uses plant-level data from the Chilean manufacturing sector (see also Alvarez and Lopez, 2004). To reiterate, the above criterion is not a classification of exportables and traditionals (which differ by country), but identifies farms' willingness and ability to participate in exportable production.

Farm-level data are obtained from the VI Chilean Census of Agriculture (1997) conducted by the Chilean National Institute of Statistics (CNIS), which is the only agricultural census since 1976. Data include location of farm (county and region), number of employees, area and production of individual crops and animal products, total land area and demographic information on farm households including age (experience) and size. The database has over 300,000 farms. However, we face the problem of farms producing some of exportables (15) and traditional (12) crops as well as products not included in either list.[2] Therefore, we select a set of farms that only produce at least one of the fifteen fruits or one of the twelve traditional crops, and that are not involved in any other crop or animal production.[3] The sampled farms use land to only produce either selected traditional crops or exportable fruits, but do not have land allocated to produce other crops or fruits.[4] Thus, farms that have land for producing vegetables, seeds, flowers, annual or permanent pastures and forages (dairy or cattle farms) are eliminated. The resulting sample of 13,478 farms could still be producers of other products because they have some land that is classified as "land for other uses." So, we select farms that have an area for other uses less than or equal to the 25 percent of total land area. The application of the above selection criteria yielded a sample of 8,284 farms.[5] Table 3.1 presents the list of exportables and traditionals with the number of farms that produce them. Figure 3.1 depicts the geographic distribution of farms according to market orientation. The traditional oriented producers (a) are located mainly in the central zone, but the export oriented producers (b) are located in the north and central zone.

The primary farm-specific characteristic in the vector X_j in equation (5) is the farm-level productivity or efficiency index (Coelli, Rao and Battese, 1998). Using data envelopment analysis (DEA) farms are ordered according to their technical efficiency, which is defined as the distance to the production frontier. Formally, an output-oriented measure of technical efficiency (TE) of each decision making unit or farm is specified as a linear programming problem:

$$
(6) \quad
\begin{aligned}
& TE_j(q^j, r^j \mid V, S) = \max_{\theta, z} \theta \\
& s.t. \quad \theta q^{jm} \leq \sum_{j=1}^{J} z^j q^{jm}, \qquad m = 1, \dots, M, \\
& \qquad \sum_{j=1}^{J} z^j r^{jn} \leq r^{jn}, \qquad n = 1, \dots, N, \\
& \qquad \sum_{j=1}^{J} z^j = 1; \quad z^j \geq 0 \qquad j = 1, \dots, J.
\end{aligned}
$$

where θ is the inverse of an output distance function for each farm with output set q^j (output -in tons- of 15 exportables plus 12 traditionals) and input set r^j (irrigated and nonirrigated farm area -in hectares-, and number of employees) under variable returns to scale (V) and strong disposability of inputs (S); z is the intensity vector that permits the construction of the best-practice frontier; J is the number of farms (8,284); M is the number of outputs (27); and N is the number of inputs (3).[6] The linear programming problem in equation (6) is solved for each farm. If $\theta = 1$ the corresponding farm is technically efficient; whenever $\theta > 1$, a farm's output can be increased with the same level of inputs by using better production or management practices (inefficiency).[7] The advantage of DEA is that the efficiency score is obtained by comparing an individual unit with its peers. For instance, traditional farms will be compared not only with export-oriented units but also with the more efficient traditional producers. This will result in an efficiency ranking of all units, without separating exporting and domestic-oriented farms. Other variables in the vector X_j in equation (5) include farm size represented by total land (hectares of traditional crops and exportables) and employment (number of family and hired workers); farm-owner's experience represented by age (in years); and a dummy for the presence of a manager or operator hired by the farm-owner (manager). This last variable represents the effect that a high skilled worker will have on the farm's performance.

A variable representing terms of trade between exportables and traditionals is computed based on prices from ODEPA. Price indexes can be calculated for each farm, but this approach is not feasible in the probit model because prices of traditionals are lower than those of exportables, resulting in a perfect prediction of the dependent variable. The alternative approach is to compute a county-level price index for each group, *i* = *E* (exportables) and *T* (traditionals):

(7) $$I_i^k = \sum_{s=1}^{S_i} \left(\frac{p_s^k q_s^k}{\sum_{s=1}^{S} p_s^k q_s^k} \right) p_s^k ,$$

where *k* represents counties, S_i represents the number of commodities in the *i*-th group, and p_s^k and q_s^k are the prices and quantities of the *s*-th product in *k*-th county. The terms of trade is then:

(8) $$T^k = \frac{I_E^k w_E^k}{I_T^k w_T^k}$$

where, w_E^k and w_T^k are the weights i.e., shares of exportables and traditionals in each county respectively, and $w_E^k + w_T^k = 1$. Without the weights, the higher price of exportables can be associated with a higher number of traditional farms in a county (table 3.1).

To represent Z_j^k, i.e., geographic characteristics of the *k*-th region, three different approaches are used. In the first one, specific geographic variables are identified. Data are obtained from two main sources: *The Regional Competitiveness Report, 2001* (Informe de Competitividad Regional, 2001), published by the Chilean Ministry of Economy (CME), and *The Chile-Environmental Statistics 1998-2002* (Chile – Estadísticas del Medio Ambiente 1998-2002) of CNIS.[8] The normalized indexes from these two sources measure geographic characteristics in the following categories: infrastructure, natural advantages, human capital, and government quality at the regional level. These variables take values from 0 to 1, where 1 represents a higher quantity of quality of each variable. The above representations of geographic characteristics are common to most studies of export behavior, which include either dummies for regions or continuous locational characteristics (e.g., Bernard and Jensen, 1995; Roberts and Tybout, 1997; Aitken, Hanson and Harrison, 1997). They are also consistent with the economic geography literature, which highlight the role of locational characteristics for export production (Krugman, 1991; Redding and Venables, 2003). We represent infrastructure with the non-farm capital index, which includes industrial (mining and manufacturing) capital, roads, potable water and sewer coverage. Natural advantage is represented by the soil type of a region.[9] This variable represents the quality of soils according to a standardized Chilean soil classification. It corresponds to the share of the area of best quality soils (apt to produce any fruit) in each region. The variable can take values from 0 to 100, wherein the maximum value would mean that the entire area of a region has only good quality soil. The human capital index, with values between 0 and 1, is a weighted combination of average schooling coverage, performance of schools, performance in college entry tests, workforce's years of schooling, health facilities and health indicators of workers. The government quality index ranging between 0 and 1 measures the performance of a local government in creating a favorable environment for businesses and its inhabitants.

The second alternative for capturing geographic characteristics is to use the agricultural export intensity of a location (Giles and Williams, 2000). For each county or region *k*, the export intensity is given by:

(9) $$Export\_Intensity_k = \frac{TR_f^k}{TR_f^k + TR_d^k}$$

which is the share of the exportable revenue in the total agricultural revenue (exportable and domestic products) of the *k*-th county or region. The export intensity variable can take values between 0 (domestic-market oriented) and 1 (export-market oriented). The variable in equation (9) can be specified at the county or regional level but, it is likely simultaneously determined with the export decision in equation (5). As noted earlier, our estimation procedure accounts for the possible endogeneity of regressors. Descriptive statistics on regional indexes and our sample of 8,284 farms are presented in tables 3.2 and 3.3. Descriptive statistics for the 2,244 export oriented producers and the 6,040 traditional oriented producers are presented in table 3.4a and 3.4b, respectively.

The final option for representing geographic characteristics is to use spatial concentration indexes, which measure the strength of locational forces of a particular area, i.e. natural advantages or technical spillovers, in attracting firms of a specific industry. Based on the Maurel and Sédillot (1999) approach, an index of geographic concentration that correctly accounts for adjacent spatial units is used for representing the geographical attributes of each location, e.g. counties. The main advantage of this method is that the geographic variable is the result of how similar firms assess a specific location, that is, it is an industry-specific measurement of locational attributes. For example, if soil type is important for export-oriented producers, they will locate (concentrate) in an area where this attribute is present. Unfortunately, the geographic concentration indexes cannot differentiate the specific forces that attract firms, and only an overall measurement of these forces can be obtained. However, for the purpose of this study this approach provides a very good representation of geographic characteristics. This variable is obtained by multiplying the employment share of each location or county i, s_i, by the agricultural geographic concentration index, γ_j. This results in a location-specific variable $s_i\gamma_j$, which will henceforth be referred to as "geographic concentration".

3.4 Estimation Procedure

Based on equation (5), initial versions of the binary probit model are specified to address the problem of endogenous regressors: efficiency, labor and land at the farm level, and county-level and regional export intensities in the case of geographic characteristics.[10]

Consider first the possibility that the efficiency scores are likely endogenous with the export decision. Prior theoretical and empirical analyses support the link between higher efficiency or productivity and export participation but, two competing hypotheses explain the directionality in this linkage. The first is the self-selection hypothesis, which states that only higher productivity firms will become exporters: Bernard and Jensen (1995, 1999) in the case of the United States; Clerides, Lach and Tybout (1998) for Colombia, Mexico and Morocco; Aw, Chung, and Roberts (2000) in Korea and Taiwan; Alvarez and Lopez (2004) in Chile; and Girma, Greenaway and Kneller (2004) in UK. In the case of a farm, there are extra costs associated with the production of exportable products, such as growing high-quality varieties sought by foreign markets, investing to preserve post-harvest quality costs, and transportation and related costs. These higher costs can only be afforded by high-productivity farms, making them self-select, and therefore, the decision to export is impacted by farms' efficiency. This relationship can be expressed as:

(10) $$y_{1j} = \alpha + \delta_1 y_{2j} + \beta_1 X_{1j} + \delta T_j^k + \gamma Z_j^k + u_{1j} \qquad j = 1, \ldots, n,$$

where efficiency, indexed by y_2, and a set of exogenous variables, X_1, T^k and Z^k, explain the export decision, y_1. Note that y_1 can only take the observable sign of a latent variable $q_f^{j^*}$.

The second hypothesis, learning-by-exporting, suggests that firms improve their productivity by participating in the exportable market (Clerides, Lach and Tybout, 1998; Aw, Chang and Roberts, 2000). In the case of Chilean agriculture, an export-oriented producer is exposed to demanding buyers/exporting firms, who require high-quality products to compete in international markets. Hence, farms learn from their export participation, which leads to higher productivity relative to those only producing for the domestic market:

(11) $$y_{2j} = \gamma_2 y_{1j} + \beta_2 X_{2j} + u_{2j} \qquad j = 1, \ldots, n,$$

where X_2 is a set of explanatory variables for y_2. Similarly, decisions on labor and land allocation are likely determined jointly with the decision to produce exportables. Also, the county-level and regional export intensities are likely endogenous since they represent respective aggregate export decisions.

From equations (10) and (11) it is apparent that $E(u_1 u_2) \neq 0$, and so, the application of standard binary probit methods to equation (10) will yield inconsistent parameter estimates. To test and correct for regressors' endogeneity, we utilize the two-stage conditional maximum likelihood (2SCML) procedure developed by Rivers and Vuong (1988) and applied in Wooldridge (2002). The 2SCML estimator is consistent and asymptotically efficient for probit models with continuous exogenous variables. Equations (10) and (11) can be rewritten as:

(12) $$\begin{aligned} y_{1j} &= \alpha_1 y_{2j} + \phi_1 X_{1j} + \mu_{1j} \\ y_{2j} &= \pi_2 X_j + V_{2j} \end{aligned}$$

where the first expression in equation (12) is the structural equation of primary interest, and the second expression is a reduced form equation for the endogenous continuous variable y_2. The variables X_{1j} and X_j are related by the identity:

(13) $$X_{1j} = J'X_j$$

where J is the appropriate selection matrix consisting of 1's and 0's. Rivers and Vuong (1988) assumed that the residuals in the reduced form of y_2 have a normal distribution. In the 2SCML procedure, the endogenous variable y_2 is regressed on selected instruments and all the explanatory variables of the system. Then, in the probit regression, the binary variable is regressed on y_2, explanatory variables and the residuals from the regression of y_2.

The advantage of the 2SCML procedure is that it also can be used for testing the exogeneity of continuous independent variables. Rivers and Vuong (1988) proposed a likelihood ratio (LR) test, which is given by:

(14) $$LR = -2(\ln \hat{L}_R - \ln \hat{L}_U)$$

where $\hat{L}_U$ and $\hat{L}_R$ are the log-likelihood values of the probit with and without the residuals as explanatory variables, respectively and LR has a chi-squared distribution with degrees of freedom equal to the number of endogenous variables in the probit equation. Wooldridge (2002) shows that a *t*-test of the residual's coefficient in the probit model can also validate exogeneity.

Based on the above, we test the assumption of endogeneity for three farm-specific variables: efficiency, labor and land, and two geographic indicators: county-level and regional export intensities. The instruments X_j in equation (12) for farm-specific variables included education (for efficiency), total county labor (for labor), total county land (for land) and all explanatory variables, while those for export intensities are the regional indexes reported in table 3.2.[11] The LR test rejects the null hypothesis that the farm efficiency index is exogenous (LR statistic, 61.80). A *t*-test on the coefficient of the estimated residuals (Residual_Efficiency) also confirms the endogeneity of the efficiency index. Similarly, the labor input is found to be endogenous (LR statistic, 38.54) but, we cannot reject the null that the land area of a farm is an exogenous variable. In the case of geographic indicators, we find both export intensities are endogenous and so, we drop them from all specifications (LR statistic, 144.97 and 183.61 for county and regional level, respectively). As noted earlier, the standard probit estimator is not consistent when some of the continuous exogenous variables are simultaneously determined with the export decision. In the next section, we focus on the consistent estimates from the 2SCML procedure in table 3.5.

3.5 Two-Stage Probit Results

In table 3.5, we present five versions of the two-stage binary probit model for the export decision. All five specifications include the residuals from the instrumental regressions of efficiency and labor. Model (1) is a basic specification with farm-specific characteristics and the county-level terms of trade. Model (2) includes the physical (geographic) characteristics: non-farm capital and soil type, and model (3) includes people and institutional characteristics: human capital and government quality. Model (4) includes farm-specific characteristics, county-level terms of trade and all geographic indexes.[12] Model (5) includes farm specific characteristics and the geographic concentration at a county level. This geographic concentration represents an overall measurement of the geographical attributes, so it can be considered as a control model. Results in last three rows of table 3.5 show that the log likelihood value improves in the presence of either or both sets of geographic indexes, confirming their significant role in the export decision. The pseudo R^2 indicates that the regression lines of all five models fit well the observed data (82% to 83%). Consistent with LR endogeneity tests, the statistical significance of the Residual_Efficiency and Residual_Labor reject the null hypotheses that efficiency and labor are exogenously determined in the export participation decision.[13] Furthermore, based on LR tests, model 4 fits the data best among the five alternative specifications in table 3.5.

Beginning with the coefficients on farm-specific characteristics, the coefficient on efficiency score is positive and significant in all five specifications, which is consistent with studies on export decision in the manufacturing sector (e.g., Bernard and Jensen, 1999; Helpman, Melitz and Yeaple, 2004). Firms with higher productivity participate in the exportable sector. The significance of farm-owner's age in the first four models shows that more experienced producers have a higher probability of participating in exportable production in all 4 models. The effect of the manager dummy is not significant in model 1 but, turns significantly positive in models 2, 3, and 4, which suggests that the presence of a manager in a farm has a significantly positive effect on the decision to participate in exportable production. The latter result is consistent with the skill or wage premium of exporting found in similar studies of the manufacturing sector (e.g., Bernard and Jensen, 1997). Together, the results on age and manager variables suggest that the presence of skilled labor on a farm increases its probability of export participation.

To capture the effect of farm size on export participation, we used two variables: labor and land. Focusing again on model 4, the probability of export participation is negatively affected by the number of employees in a farm. Other than the owner or manager, much of the labor employed in these farms is of the unskilled type. Not surprisingly then, the probability of export participation is negatively impacted by increases in unskilled employment. Increased mechanization of export production and harvesting to preserve quality also support the negative effect of (unskilled) employment on export participation. The coefficient on land variable is not significant in model 4, despite being negative in the other four models. It will be shown later that both size variables have weaker effects on export participation relative to other farm-specific and geographic characteristics.

The coefficient on the county-level terms of trade is significantly positive and of similar magnitude in all models. Implicit in this index are the uniform tariffs of either 31.5 or 11 percent for most traditionals, i.e., $\frac{P_E}{P_T^W(1+t)}$, where P_E represents weighted exportables' price, while the denominator corresponds to tariff-adjusted (*t*), world price of traditionals. Therefore, a reduction in tariffs on traditionals' imports will increase a farm's probability of export participation. Since Chile is a small, open economy in most international fruit markets, further increases in exportables' terms of trade likely come from outside its borders.

The effect of the physical characteristics suggests that soil type has a significantly negative effect on the probability of export participation in model 2 and 4 but, non-farm capital is significant (negative) in model 4 alone. Likewise, government quality has a significantly positive impact on the participation decision in model 3 and 4 but, the coefficient on human capital is significant (positive) in model 4 only. Model 5 shows that the geographic concentration index at the county level has a positive and significant effect on the decision to participate in the exportable production. Given that the specification in model 4 is statistically preferred to those in model 2, 3 or 5, we focus on the former. The result that higher soil quality has a significantly negative effect on the probability of export participation is likely due to the Chilean soil classification system. The Chilean soil quality index documents sidehills and uneven topography, where a significant share of exportable fruits is produced, as low-quality soils. The advantage of sidehills is that they provide better exposure to sunlight relative to even topography. Thus, the negative relationship between the probability of export participation and "low-quality soils" of sidehills does not come as a surprise (Suelos. El Principio de la Vid, 2001). As noted earlier, the reason to include the non-farm capital index in the export behavior model is the hope that it will mimic infrastructure. However, the index is dominated by the presence or absence of mining and manufacturing capital with little impacts from roads and other public infrastructure components. Therefore, the higher the non-farm capital endowment, the lower is the probability of agricultural export participation.[14]

The human capital index, which is a source of productivity spillovers to the agricultural sector, has a positive and statistically significant effect on the participation decision (model 4). Note that educational infrastructure and years of schooling of inhabitants are key components of the human capital index. So, our results from model 4 confirm the significant role of productivity not only at the farm level but also at the regional level in the decision to participate in exportable production. The quality of regional government has a statistically significant positive effect on the probability of export participation. Thus, regions with better local governmental performance appear to provide favorable conditions, which promote export production in agriculture.

It is important to note that data availability limits the proposed specification (equation 5) to investigate export participation of Chilean farms. For instance, information on farms' land/soil quality is not available, which may affect our ranking of farms using the DEA. We believe that the effect of possible (farm-specific) omitted variables can be partially captured by either the geographic concentration variable or soil-quality indicators at the regional level.

Productivity versus Geographic Effects

The discussion earlier on the coefficients of the export participation model focuses on directionality rather than the relative strength of effects of farm-specific and geographic characteristics. To infer on the relative effects, marginal effects are computed for each of the explanatory variable in model 4 of table 3.5. Formally, the marginal effect of X_{jl}, the l^{th} element of X_j, is:

(15) $$\frac{\partial \Phi(\beta' X_j)}{\partial X_{jl}} = \phi(\beta' X_j)\beta_l,$$

where the partial derivative of the non-linear cumulative distribution function with respect to a particular variable (X_{jl}) will depend on the level at which the other independent variables are evaluated (Wooldridge, 2002). Thus, marginal effects of X_{jl}

depend on the levels of other variables in X_j. To alleviate this problem, predicted probabilities of export participation arising from each variable included in model (4) of table 3.5 are derived as:

$$\hat{P}(y = 1 | \overline{X}_j,\ X_{jl}) = \Phi(\hat{\beta}' X_j) \tag{16}$$

where $\hat{P}(.)$ is the predicted probability when all variables are evaluated at their respective means, except X_{jl}. Thus, holding all other variables at their means, the effect of changing X_{jl} on export participation can be illustrated with a plot of $\hat{P}(.)$.

Figures 2, 3 and 4 show the predicted probabilities of export participation due to changes in each of the farm-specific and geographic characteristics, and the terms of trade. The graphical analysis permits us to identify the relative strength of factors influencing the participation decision and focus our discussion on key determinants of export behavior. Among the farm-specific characteristics, the marginal effects corresponding to efficiency scores and the manager dummy are larger relative to other variables. In particular, the marginal effects of efficiency show an interesting pattern, where the predicted probabilities are positive only after a certain threshold, which is approximately equal to the sample mean of efficiency scores (0.709, table 3.3). Similarly, age and the manager dummy charts show increasing predicted probabilities, while that of the labor show a downward trend. Figure 3.3 shows that favorable terms of trade to exportables has a relatively strong effect on export participation. Among the geographic variables, the predicted probabilities with regard to the government and human capital indexes have a positive slope, while those of non-farm capital and soil type show a weak negative trend.

Based on predicted probabilities in figures 2, 3 and 4, we focus on the marginal effects of two key variables of interest: efficiency and human capital, which represent productivity at farm and regional levels, respectively. Table 3.6 presents four possible scenarios: case 1 evaluates the marginal effects when all variables are evaluated at their respective means, the most commonly reported results in the discrete choice literature (Wooldridge, 2002; Aitken, Hanson and Harrison, 1997); case 2 evaluates the marginal effects holding the human capital index at 0.9 and the rest of the variables at their respective means; case 3 holds the efficiency score at 0.9 and others at respective means; and case 4 evaluates marginal effects holding the efficiency score and human capital index at 0.9 and the other variables at their respective means.

Case 1 shows that efficiency has the largest marginal effect (2.029) followed by that of the manager dummy (0.480), government quality (0.279), and human capital (0.206). In case 2, holding the human capital index at 0.9 strengthens the marginal effects of farm-level efficiency (5.831), manager (1.378), government quality (0.803), and human capital (0.593). Evaluating marginal effects when the efficiency score is held at 0.9, case 3, also shows a similar ranking of farm-specific and geographic characteristics: efficiency (1.123), manager (0.265), government quality (0.155) and human capital (0.114) indexes. When both efficiency and human capital effects are combined, one would anticipate that the probability of export participation will likely increase more than those in case 2 and 3. Alternatively, a highly efficient farm is expected to show a higher probability of export participation when located in a region with better geographic characteristics relative to that in a region with no such advantages. However, the marginal effects in case 4 are lower than those of case 1, 2 or 3. These results arise from the nonlinearity inherent in discrete choice models (Wooldridge, 2002). To further clarify this situation, figures 5(a) and 5(b) plot the predicted probabilities of efficiency when human capital is evaluated at different levels (keeping all other variables at their mean) and the predicted probabilities of human capital when efficiency is evaluated at different levels. Clearly, an increase in the overall productivity of a location will reduce the threshold that is necessary for a farm to become an export-oriented producer. On the other hand, an increase in the individual productivity of farms will increase the probability that a location will create a favorable environment to produce exportables. In this case, not only does the threshold of the human capital index changes, but also the slope of its predicted probabilities. Thus, the lower marginal effects of case 4 arise from the slope changes of predicted probabilities, especially that of the human capital index, illustrated in figure 3.5(b). Therefore, evaluating both efficiency and human capital indexes near respective maxima implies exhaustion of incentives or the potential to further induce a farm to produce exportables. A similar illustration is obtained when predicted probabilities of efficiency are evaluated at alternative levels of government quality and vice versa.

Based on figures 5(a) and 5(b), we also quantify the impact of individual and locational productivity, i.e., efficiency and human capital, on the decision to participate in exportable production. In general, the effect of changes in farm-specific productivity is stronger than the effect of the locational productivity on export participation. For example, if the human capital index increases from 0.75 to 0.90, the productivity of farms is affected in a way that lowers the threshold required for export participation as shown in figure 3.5(a). On the other hand, if the efficiency score increases from 0.75 to 0.90, then the effect on predicted probabilities of the human capital index is greater than the effect produced by a corresponding change in itself, i.e., a comparison of figure 3.4(c) and 3.5(b). Alternatively, if a farm increases its productivity, its probability of export participation will be higher than when the overall productivity of its surroundings increases. Moreover, to participate in exportable production, a farm has to satisfy a minimum efficiency threshold. In other words, even when the geographic characteristics favor exports, if a farm does not meet the efficiency threshold, its probability of participating in exportable production will not increase.

The geographic concentration variable captures locational attributes (natural advantages and spillovers). So, we also evaluate the relative impact of firm-specific and geographic variables on export participation using model 5. Figure 3.6 shows that the probability of export participation increases with the strength of locational forces. Figures 7(a) and 7(b), which are based on an analysis similar to that in figures 5(a) and 5(b), shows the robustness of our earlier results. That is, farm-specific efficiency has a stronger effect on export participation of Chilean farms than the combined geographic forces.

In sum, farm-level efficiency, skilled labor, regional human capital, and government quality are key factors increasing the likelihood that a Chilean farm participates in exportable production. Improvements in exportables terms of trade favor export participation but, this effect might be limited since Chile is a small, open economy in most fruit markets. More importantly, a minimum farm efficiency threshold would be required for geographic characteristics to positively impact the probability of export participation.

3.6 Summary and Conclusions

In this article, we analyze Chilean farms' export participation and the relative importance of farm-specific and geographic characteristics in this decision. The Chilean example can provide insights into factors correlated with the successful transformation of protected trade regimes into open, market-based agricultural economies elsewhere.

Based on prior literature, an export behavior model is estimated using data on 8,284 Chilean farms for 1997. Farm-specific characteristics (efficiency, size and ownership structure), an indicator for terms of trade between exportables and traditionals, and geographic characteristics (e.g., education, institutional quality) are considered in farms' export behavior. Since prior literature has addressed simultaneous determination of export decision and firm characteristics, we test and correct for possible endogeneity (e.g., efficiency, labor) of regressors using a two-stage conditional maximum likelihood procedure.

Results suggest that trade liberalization, i.e., lowering tariffs on traditional commodities, improves the terms of trade of exportables, which significantly affects Chilean farms' decision to produce exportables. Farm-specific efficiency effects appear relatively stronger than the combined effects of geographic characteristics on export participation. When a highly efficient farm locates in a region with better geographic characteristics, its likelihood of producing for export markets is higher.

On the other hand, opposite results are obtained when low-efficiency farms are located in regions with higher human capital or government quality. The latter is due to an efficiency threshold for farms to participate in exportable production.

Skilled labor is related to a higher probability of producing for the export market, while unskilled labor has the opposite effect. The effects of other farm and geographic characteristics such as farm-owner's age, land and soil type appear to be lower than that of farm efficiency and regional human capital. Also, local governments that create a favorable environment for businesses have a positive impact on the farm's decision to produce exportables.

Unless farms achieve a minimum efficiency level, investments in regional productivity or infrastructure appear to have relatively little effect on export participation. Exporting is positively associated with profits and income, and to create successful exporters, a farm's efficiency is relatively more important than the characteristics of the region within which it operates. The results on productivity highlight the role that government policies could have in transforming domestic-market oriented farms into export producers. Future research would evaluate the impact of alternative policies on productivity and other firm-specific charactersistics for further transforming Chilean agriculture and improving farmers' welfare.

BIBLIOGRAPHY

Agosin, M. 1999. “Trade and Growth in Chile”. *CEPAL Review* 68: 79-100.

Aitken, B., G.H. Hanson and A.E. Harrison. 1997. “Spillovers, Foreign Investment and Export Behavior.” *Journal of International Economics*, 43(1): 103-132.

Aksoy, A.M., and J.C. Beghin. 2005. *Global Agricultural Trade and Developing Countries*. Washington DC: The World Bank Press.

Alvarez, R. and R. Lopez. 2004. “Orientacion Exportadora y Productividad en la Industria Manufacturera Chilena.” *Cuadernos de Economia* 41(124): 315-343.

Avendaño, O. 2001. “Diferenciacion y Conflicto en el Empresariado Agricola Chileno. Periodo 1975-1998”. Debates y Reflexiones. Aportes para la Investigacion Social. Universidad de Chile, Programa de Estudios Desarrollo y Sociedad. Document No 3.

Aw, B.Y., S. Chung, and M.J. Roberts. 2000. “Productivity and Turnover in the Export Market: Micro-Level Evidence from the Republic of Korea and Taiwan (China).” *World Bank Economic Review* 14(1): 65-90.

Aw, B.Y., and A. R. Hwang. 1995. “Productivity and the export market: A firm-level analysis.” *Journal of Development Economics* 47(2): 313-332.

Bernard, A.B., J. Eaton, J. B. Jensen, and S.S. Kortum. 2003. Plants and Productivity in International Trade. *American Economic Review* 93(4): 1268-1290.

Bernard, A.B. and J. B. Jensen. 1995. “Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987.” *Brookings Papers on Economic Activity, Microeconomics*. 1995: 67-119.

Bernard, A.B. and J. B. Jensen.. 1997. “Exporters, Skill Upgrading and the Wage Gap” *Journal of International Economics* Vol. 42(3): 3-31.

Bernard, A.B. and J. B. Jensen. 1999. “Exceptional Exporter Performance: Cause, Effect, or Both?” *Journal of International Economics* Vol. 47(1): 1-26.

Bernard, A.B., J. Eaton, J. B. Jensen, and S.S. Kortum. 2003. Plants and Productivity in International Trade. *American Economic Review* 93(4): 1268-1290.

Bernard, A.B. and J. B. Jensen. 2004a. “Why Some Firms Export.” *Review of Economics and Statistics* 86(2): 561-569.

Bernard, A.B. and J.B. Jensen. 2004b. “Exporting and Productivity in the USA.”

Oxford Review of Economic Policy 20(3): 343-357.

Clerides, S., S. Lach and J. Tybout. 1998. "Is Learning By Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco." *The Quarterly Journal of Economics* 113(3): 903-947.

Coelli, T.J., D.S.P. Rao, and G.E. Battese. 1998. *An Introduction to Efficiency and Productivity Analysis.* Boston: Kluwer Academic Publishers.

Cohen, J.P., and C.J. Morrison Paul. 2004. "Public Infrastructure Investment, Interstate Spatial Spillovers and Manufacturing Costs." *Review of Economics and Statistics* 86(2):551-560.

Giles, J.A. and C.L. Williams. 2000. "Export-led growth: a survey of the empirical literature and some non-causality results." Part I. *Journal of International Trade and Economic Development* 9(3): 261-337.

Girma, S., D. Greenaway, and R. Kneller. 2004. "Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms." *Review of International Economics* 12(5): 855-66.

Helpman, E., M. Melitz and S. Yeaple. 2004. "Export Versus FDI with Heterogeneous Firms." *American Economic Review* 94(1): 300-316.

Krugman, P, 1991. *Geography and Trade*. Cambridge, MA: MIT Press.

Limao, N. and A.J. Venables. 2001. "Infrastructure, Geographical Disadvantage and Transport Costs." *World Bank Economic Review* 15(3): 451-479.

Maurel, F. and B. Sedillot. 1999. "A Measure of the Geographical Concentration in French Manufacturing Industries." *Regional Science and Urban Economics* 29: 575-604.

Melitz, M. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71(6): 1695-1725.

ODEPA, 2001. *Compendio Estadístico Silvoagropecuario* 1990-2000.

Pavcnik, N. 2002 "Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants." *Review of Economic Studies* 69(1): 245-76.

Portilla, B. 2000. "La Política Agrícola en Chile: Lecciones de Tres Décadas." Serie Desarrollo Productivo 68. Economic Commission for Latin America and the Caribbean.

Redding S. and A.J. Venables. 2003. "Geography and Export Performance: External Market Access and Internal Supply Capacity." Working Paper, 9637, National Bureau of Economic Research, Cambridge, MA.

Richardson, J.D. and K. Rindal. 1995. Why Exports Really Matter! The Institute for International Economics, Washington DC.

Rivers, D. and Q. Vuong. 1988. "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models." *Journal of Econometrics*, 39(3):347-366.

Roberts, M. and J. Tybout. 1997. The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs. *American Economic Review*, 87(4):545-564.

Saéz. S. and J.G Valdés. 1999. "Chile and its Lateral Trade Policy". CEPAL Review 67. Economic Commission for Latin America and the Caribbean.

Suelos. El Principio de la Vid. 2001. Vendimia. 2001. 3(20).

Wagner, J. 2005. "Exports and Productivity: A survey of the Evidence from Firm Level Data." University of Lüneburg, Working Paper 4.

Wooldridge, J. M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.

World Bank. 2001. "Chile: Poverty and Income Distribution in a High-Growth Economy 1987-1998." Report No. 22037-CH, August 30, Washington D.C.

Table 3.1. List of Traditionals and Exportables (Chile, 1997)

Fruit or Crop	Number of Farms
Traditionals	
Wheat	3723
Durum Wheat	126
Barley	85
Oat	748
Rice	118
Potato	1593
Dry Bean	812
Lentil	106
Rape	8
Pea	26
Lupine	184
Sugar Beet	947
Total Farms with Domestic-Market Oriented Crops*	6040
Exportables	
Almond	119
Blueberry	3
Plum	77
Apricot	86
Peach	368
Kiwi	84
Raspberry	179
Red Apple	132
Green Apple	107
Orange	61
Nectarine	85
Walnut	175
Avocado	855
Pear	79
Table Grape	547
Total Farms with Export-Market Oriented Fruits*	2244
Total Number of Farms in the Sample	8284

* The sum of farms that produce fruits or crops does not match the total number of farms because a farm can produce more than one product.

Table 3.2. Geographic Characteristics

Region	Non-Farm Capital	Soil type (%)	Human Capital	Government Quality
1	0.48	0.41	0.78	0.28
2	1.00	0.00	0.84	0.30
3	0.77	0.79	0.63	0.68
4	0.35	1.98	0.49	0.60
5	0.76	4.95	0.92	0.13
6	0.31	11.70	0.28	0.19
7	0.08	15.45	0.26	0.26
8	0.68	13.89	0.50	0.49
9	0.14	19.61	0.00	0.00
10	0.00	23.06	0.36	0.62
11	0.07	0.03	1.00	0.36
12	0.63	0.00	1.00	0.46
13	0.87	8.13	0.93	1.00

Table 3.3. Descriptive Statistics of Farm-Specific and Geographic Characteristics (8,284 Farms)

	Mean	Standard Deviation	Minimum	Maximum
Efficiency	0.709	0.229	0.0063	1
Age	48.551	14.228	18	99
Manager	0.078	0.269	0	1
Education	9.308	4.023	0	17
Labor	3.231	8.008	1	170
Land	8.212	35.248	0.07	1029
County-Level Terms of Trade	80.567	297.109	0.01	1795
County Export Intensity	0.265	0.366	0	1
Region Export Intensity	0.270	0.334	0	0.85
Non-Farm Capital	0.409	0.313	0	1
Soil Type	13.407	5.412	0.0033	23.05
Human Capital	0.419	0.326	0	1
Government	0.304	0.272	0	1
Geographic Concentration (x 1000)	-0.01173	0.011704	-0.05253	-0.00003

Table 3.4a. Descriptive Statistics of Farm-Specific and Geographic Characteristics of Export Oriented Producers (2,244 Farms)

	Mean	Standard Deviation	Minimum	Maximum
Efficiency	0.942	0.077	0.75188	1
Age	54.262	13.594	18	95
Manager	0.213	0.410	0	1
Education	11.512	4.332	0	17
Labor	5.936	13.072	1	170
Land	7.467	20.261	0.07	777.6
County-Level Terms of Trade	292.157	513.983	0.03	1795.81
County Export Intensity	0.778	0.222	0.00046	1
Region Export Intensity	0.705	0.238	0.00084	0.85634
Non-Farm Capital	0.642	0.259	0	1
Soil Type	6.894	4.031	0.0033	23.05
Human Capital	0.765	0.260	0	0.93
Government	0.361	0.336	0	1
Geographic Concentration (x 1000)	-0.012	0.012	-0.05253	-0.000031

Table 3.4b. Descriptive Statistics of Farm-Specific and Geographic Characteristics of Traditional Oriented Producers (6,040 Farms)

	Mean	Standard Deviation	Minimum	Maximum
Efficiency	0.623	0.207	0.00626	1
Age	46.430	13.872	18	99
Manager	0.029	0.167	0	1
Education	8.489	3.573	0	17
Labor	2.226	4.557	1	155
Land	8.489	39.387	0.1	1029
County-Level Terms of Trade	1.957	11.726	0.01	428.68
County Export Intensity	0.074	0.177	0	0.9289
Region Export Intensity	0.109	0.189	0	0.85633
Non-Farm Capital	0.323	0.287	0	1
Soil Type	15.828	3.538	0.0033	23.05
Human Capital	0.291	0.245	0	1
Government	0.283	0.242	0	1
Geographic Concentration (x 1000)	-0.012	0.012	-0.05253	-0.000031

Table 3.5. Two-Stage Binary Probit Specifications for Export Participation

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-17.727*	-13.417*	-18.941*	-15.190*	-17.771*
	(0.594)	(0.920)	(0.720)	(1.057)	(0.604)
Residual_Efficiency	-12.323*	-8.317*	-12.876*	-8.292*	-12.371*
	(0.586)	(0.818)	(0.782)	(1.098)	(0.591)
Residual_Labor	0.059*	0.036	0.361*	0.553*	-0.031
	(0.028)	(0.031)	(0.052)	(0.095)	(0.029)
Farm Specific Characteristics					
Efficiency	20.728*	16.849*	22.417*	18.677*	21.025*
	(0.760)	(0.954)	(0.990)	(1.207)	(0.776)
Age	0.021*	0.015*	0.027*	0.029*	0.017*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Manager	0.412	0.534*	2.630*	4.414*	0.246
	(0.237)	(0.250)	(0.380)	(0.730)	(0.242)
Labor	-0.060*	-0.025	-0.359*	-0.541*	0.032
	(0.028)	(0.031)	(0.052)	(0.095)	(0.029)
Land	-0.018*	-0.016*	-0.006*	0.005	-0.022*
	(0.002)	(0.002)	(0.002)	(0.004)	(0.001)
Terms of Trade	0.014*	0.011*	0.011*	0.010*	0.013*
(County-Level)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Geographic Concentration					21192.99*
(County Level)					(2381.19)
Geographic Characteristics					
Non-Farm Capital		0.034		-2.664*	
		(0.177)		(0.613)	
Soil Type		-0.104*		-0.074*	
		(0.018)		(0.019)	
Human Capital			-0.288	1.899*	
			(0.290)	(0.666)	
Government Quality			1.793*	2.572*	
			(0.308)	(0.448)	
Number of observations	8284	8284	8284	8284	8284
LR chi-squared statistic[1]	7945.65*	8035.44*	8035.54*	8070.84*	8031.53*
Log-likelihood value	-866.157	-821.256	-821.209	-803.563	-823.216
Pseudo R^2	0.8210	0.8303	0.8303	0.8339	0.8299

Numbers in parentheses are standard errors; * denote statistical significance at the 5% level. [1]Test statistic has 8, 10, 10, 12 and 9 degrees of freedom for each model, respectively.

Table 3.6. Marginal Effects From Two-Stage Probit Model (4)

	Case 1	Case 2	Case 3	Case 4
Efficiency	2.029	5.831	1.123	0.126
Labor	-0.059	-0.169	-0.033	-0.004
Land	0.001	0.002	0.000	0.000
Age	0.003	0.009	0.002	0.000
Manager	0.480	1.378	0.265	0.030
County-Level Terms of Trade	0.001	0.003	0.001	0.000
Non-farm Capital	-0.289	-0.832	-0.160	-0.018
Soil Type	-0.008	-0.023	-0.004	-0.001
Human Capital	0.206	0.593	0.114	0.013
Government Quality	0.279	0.803	0.155	0.017

Case 1: All variables at mean;
Case 2: Human Capital at 0.9, Rest at respective mean;
Case 3: Efficiency at 0.9, Rest at respective mean;
Case 4: Efficiency at 0.9, Human Capital at 0.9, Rest at respective mean.

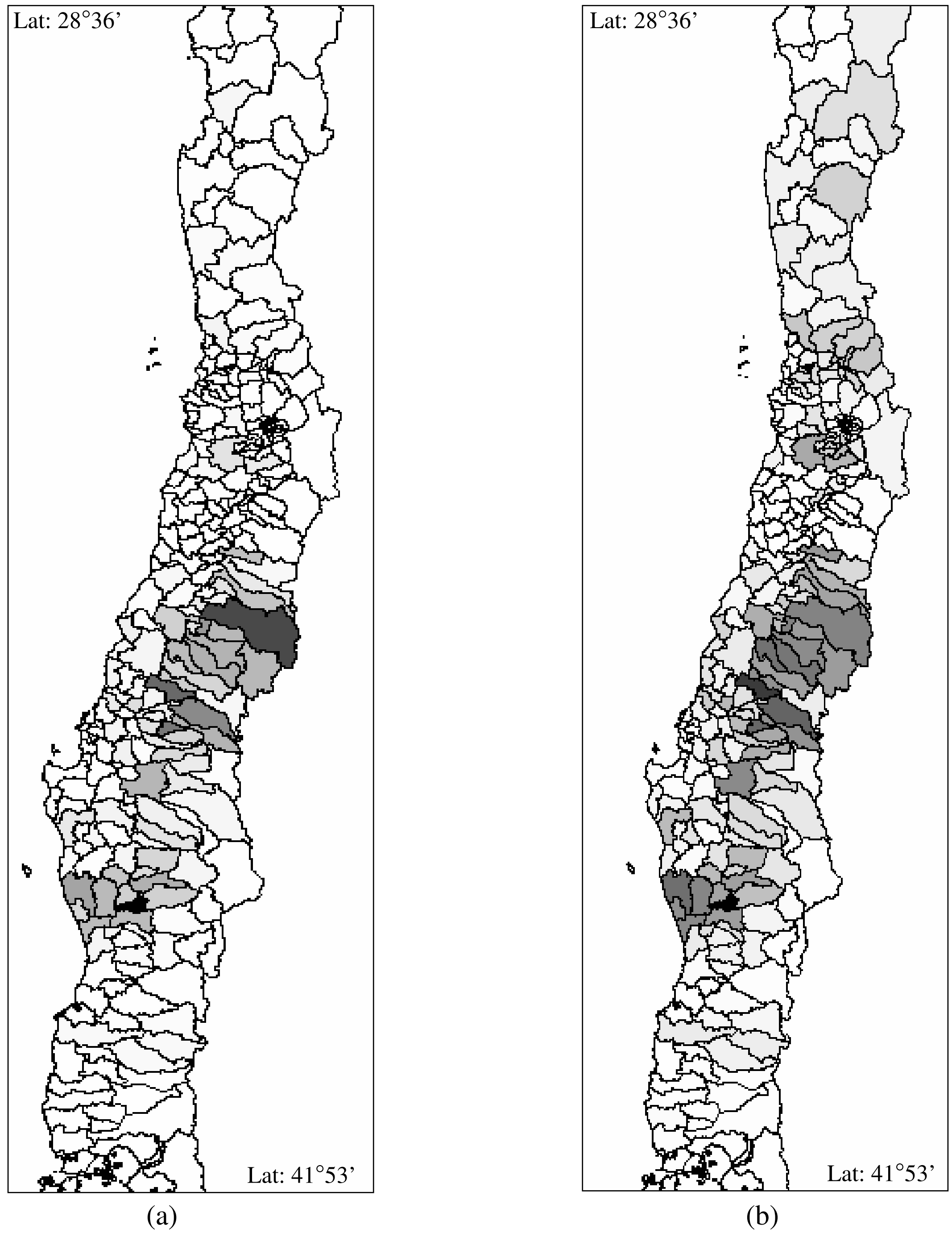
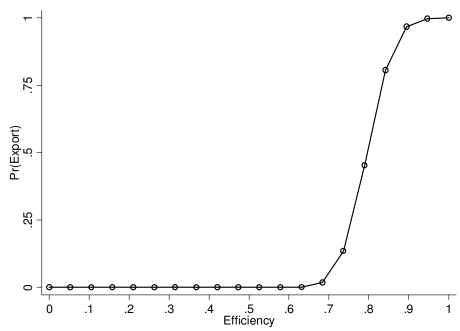
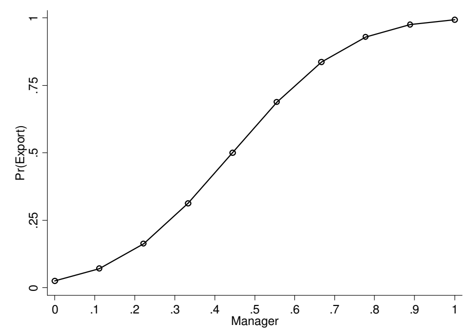


Figure 3.1: Geographic Distribution of Farms According to Market Orientation*

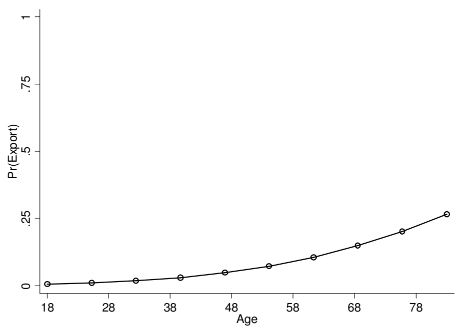
* For graphical convenience only the central zone is shown. This zone concentrates most farmers. Darkness regions represent a higher concentration of farms.



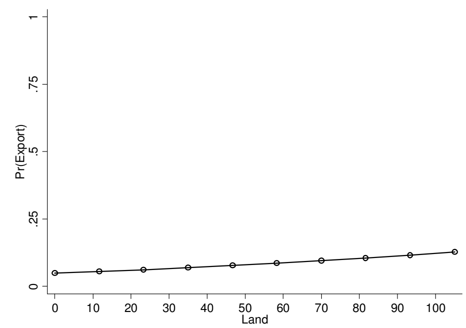
(a) Efficiency



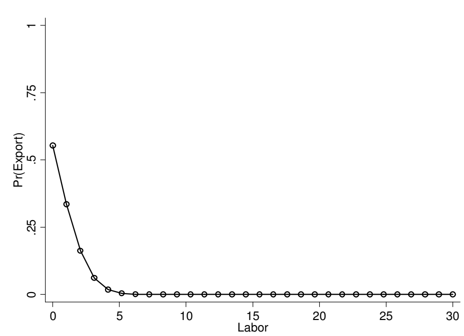
(b) Manager



(c) Age



(d) Land



(e) Labor

Figure 3.2: Predicted Probabilities Due to Changes in Farm-Specific Characteristics

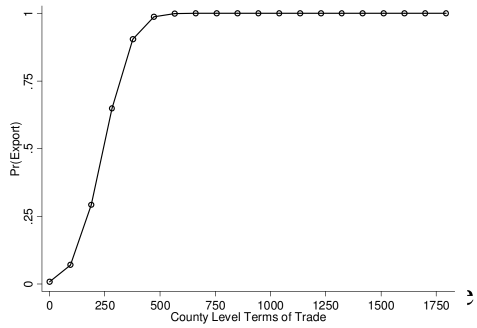


Figure 3.3: Predicted Probabilities Due to Changes in County-Level Terms of Trade

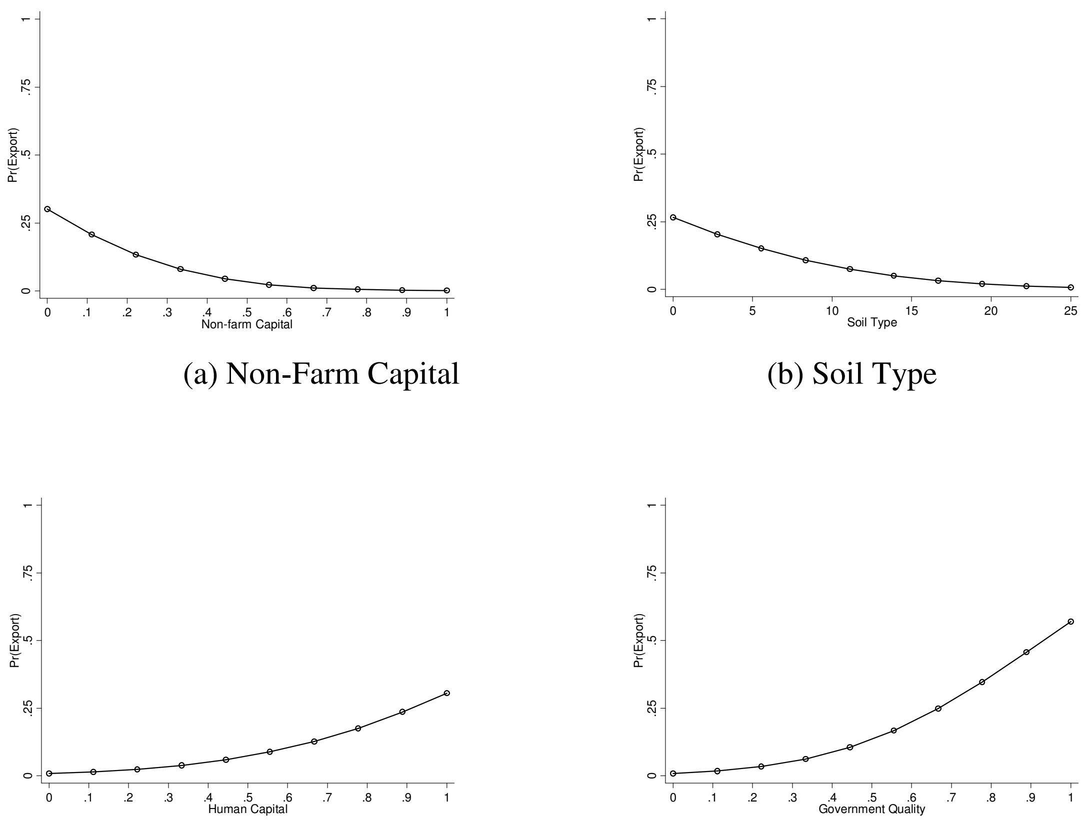
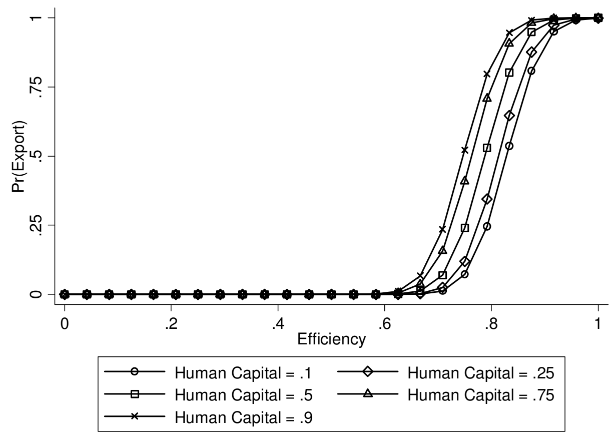
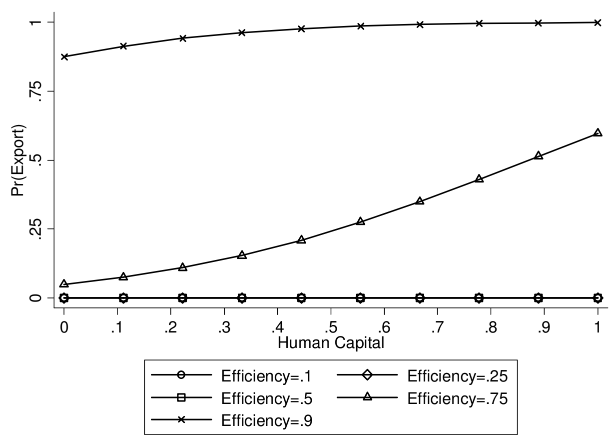


Figure 3.4: Predicted Probabilities Due to Changes in Geographic Characteristics

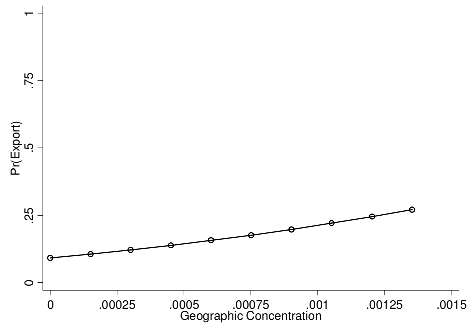


(a)



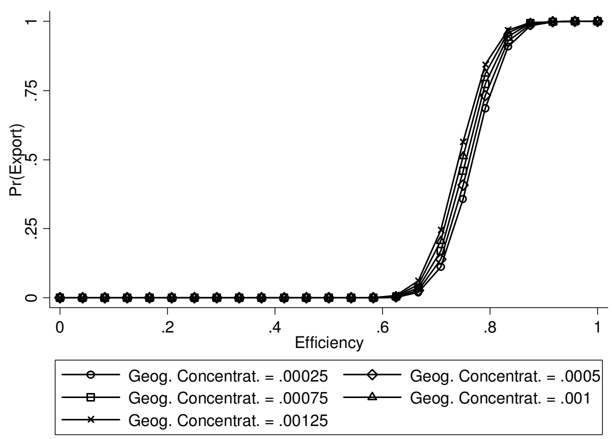
(b)

Figure 3.5: Predicted Probabilities of Alternative Efficiency and Human Capital Indexes

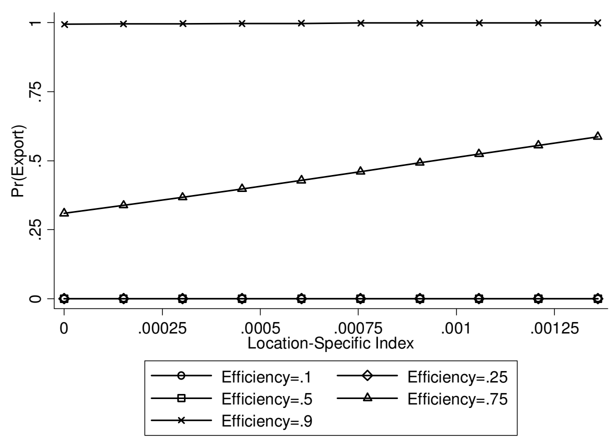


Geographic Concentration

Figure 3.6: Predicted Probabilities Due to Changes in Geographic Concentration



(a)



(b)

Figure 3.7: Predicted Probabilities of Alternative Efficiency and Geographic Concentration

ENDNOTES

[1]Similar to Aitken, Hanson and Harrison (1997), we have a static export-behavior model based on distribution-cost differences. Roberts and Tybout (1997), Bernard and Jensen (2004), Helpman, Melitz and Yeaple (2004) and others find evidence of sunk costs in firms' export decision. Such dynamic considerations are beyond the scope of this article since we have cross-sectional data. Note also that the cited literature reports both cross-sectional and time-series results (e.g., Bernard and Jensen, 1995).

[2]It is not possible to group farms by specific crops or fruits (e.g., grapes) since they produce more than one product.

[3]A key question addressed in this study is whether or not higher productivity causes participation in exportable production. A measure of productivity should reflect the true, overall farm efficiency of using inputs to generate outputs. Situations where a farm could be inefficient producing an exportable fruit, but highly efficient producing a non-exportable fruit should therefore be avoided.

[4]In an alternative multinomial logit model, with a sample that also included farmers producing exportable and traditional products, the independent of irrelevant alternative assumption was rejected. As a result, a binary setting is used, which also allows for testing possible endogeneity.

[5]The 25 percent cutoff had an effect on our sample size. Setting the cutoff to zero or 50 percent produced a sample of 4,430 or 13,478 farms but, did not affect the quality of our results in the next section.

[6]It is assumed that the intensity of intermediate inputs (e.g., fertilizers and chemicals) in agricultural production is the same for all farms in our sample.

[7]The efficiency scores under the constant and variable returns to scale assumptions are of similar magnitude. Reported results in the next section are quantitatively and qualitatively similar to those obtained under constant returns to scale. We represent efficiency scores using $1/\theta$, where inefficient farms have scores less than 1.

[8]These reports contain data for several years including 1997. In our estimation, data from only 1997 are used. The CME report also contains other non-farm characteristics (e.g., firm performance, R&D), which are not included in our study.

[9]Natural advantages specific to the region can be measured by factors such as type of soil, temperature, precipitation, and topography. We chose soil type since there exists an established scientific classification of soils based on potential uses or use capacities.

[10]The estimation used STATA, Version 8.

[11]The lack of additional instruments preclude us from testing the endogeneity of geographic characteristics. Manager is a dummy variable and so, the Rivers and Vuong (1997) procedure is not applicable.

[12]Other combinations of geographic and farm-specific characteristics neither improved the fit nor significantly altered results in table 3.3.

[13]In the case of model 2, Residual_Labor is significant at the 10% level.

[14]High correlation of non-farm capital with other available indexes in the CME report, and the long and narrow landscape of Chile make it harder to further decompose the effects of components of some these indexes. For a discussion of the difficulties in quantifying infrastructure effects in the context of US manufacturing sectors, see Cohen and Morrison Paul (2004).

CHAPTER FOUR

EXPORT BEHAVIOR IN THE CHILEAN FOOD PROCESSING INDUSTRY: THE ROLE OF PRODUCTIVITY AND GEOGRAPHY

4.1 Introduction

In the current wave of globalization, exports are often viewed as indicators of efficiency and performance. The positive correlation between exports and economic growth has led to a flurry of export promotion activities by developed- and developing-country governments (Frankel and Romer, 1999; Giles and Williams, 2000; Easterly, 2004; Dollar and Kraay, 2004). Since export subsidies are being phased out (Uruguay/Doha Round of WTO negotiations), many of these promotional activities are aimed at helping firms/producers overcome informational asymmetries, knowledge spillovers, and credit and exchange rate risks. Yet the factors that underlie a firm's decision to export, continue to export or exit a foreign market have received limited attention until recently (Bernard and Jensen, 1995; See Wagner, 2005, for a summary). Part of the problem is that the export-led growth theory has been mostly macroeconomic in design and applications. The small number of firm-level export studies reflects problems of data availability as well as the limited understanding of the characteristics of exporting firms, which are critical to the design of an effective policy to encourage trade participation (Bernard and Jensen, 1997, 1999; Roberts and Tybout, 1997; Helpman, Melitz and Yeaple, 2004).

The purpose of this essay is to improve our understanding of firms' export behavior using a panel database from the Chilean food processing sector. With much of its exports activity in the agricultural and food sectors, Chile has often been cited as one of the best examples of the export-led growth concept. In this study, we will investigate the relative importance of firm-specific and geographic characteristics in Chilean firms' export behavior. To achieve this objective, a model of firm export behavior is derived from the dynamic-profit-maximizing framework of Roberts and Tybout (1997). Here, firms' export decision depends crucially on profits net of sunk (entry and/or exit) costs. The Chilean Annual National Manufacturing Survey (ENIA) is the source of our panel data on food processing firms from 1998 to 2003. A key firm-specific characteristic, i.e., firm productivity is derived using a nonparametric approach. Following Maurel and Sedillot's (1999) approach, a geographic concentration index, which accounts for economic activity in adjacent spatial units, is derived. We then estimate a probit model of export decision and a truncated regression model of export intensity as functions of firm-specific and geographic characteristics.

The next section presents a brief review of the recent literature on export decision models. Then, an outline of our empirical methodology is given prior to the description of data including productivity computations. The discussion of results is followed by a summary and conclusions.

4.2 Prior Literature

Beginning with the seminal contribution of Bernard and Jensen (1995) and Aw and Hwang (1995) a vast and prolific field of empirical trade research using firm-level data has emerged during the past decade. In the U.S. manufacturing sector, Bernard and Jensen (1995) found that exporting firms are larger, more productive, more capital intensive, and pay higher wages than the non-exporters. Using firm-level data from the Taiwanese electronic industry, Aw and Hwang (1995) found that export-oriented firms had higher productivity levels relative to the domestic-market-oriented ones. Recent research has concentrated on evidence of the differences between exporters and non-exporters and the causes that lead to exporters' higher productivity. A complete survey of the firm-level literature can be found in Wagner (2005).

Two hypotheses have been proposed to explain the higher productivity of exporters relative to that of the other firms. The first hypothesis is based on a self-selection process by firms themselves. Exporting requires extra resources in the form of transportation, distribution and marketing costs, workers with foreign managerial skills, and modification of domestic products for external markets. These costs impose a barrier that only the more productive firms can afford (Bernard and Jensen, 2004a). Hence, high-productivity firms self-select into export markets. Evidence supporting this hypothesis can be found in Bernard and Jensen (1999); Clerides, Lach and Tybout (1998) for Colombia, Mexico and Morocco; Aw, Chung, and Roberts (2000) in Korea and Taiwan; Alvarez and Lopez (2004) in Chile; Girma, Greenaway and Kneller (2004) in UK; and Delgado, Farinas and Ruano (2002) in Spain. The second hypothesis is based on the idea that firms can improve their productivity by capturing knowledge and technical spillovers through their participation in international markets. Exporters face demanding traders or buyers who require improved production and marketing processes. Besides, the contact with high quality input suppliers gives firms an opportunity to improve their productivity. Hence, firms undergo a learning-by-exporting process which can lead to higher productivity relative to those producing only for the domestic market. However, evidence supporting this hypothesis is mixed. Some studies show that there is a positive effect of exporting on productivity, but this evidence is insignificant when compared to that on self-selection (Clerides, Lach and Tybout, 1998; Aw, Chung and Roberts, 2000).

Despite the empirical evidence, only in the last few years have there been theoretical models developed to formally explain a firm's decision to export. Roberts and Tybout (1997) proposed a dynamic model in which profit maximizing firms incur fixed or sunk (entry/exit) costs if they want to export. Thus, the extent of such sunk entry- or exit-costs determines a firm's decision to export. Note that transitory policy changes or macro shocks, e.g. exchange rates changes, could also induce firms to enter or exit foreign markets, so long as such changes yield revenues in excess of sunk costs to make exporting profitable. Yeaple (2005) presents a general equilibrium model of the export decision in which identical homogenous firms can choose to produce with different available technologies, and are free to hire workers of different skill levels. Firm heterogeneity is the result of some firms adopting a new low unit-cost technology with a fixed cost and hiring more skilled workers. In the presence of trade costs, only low-cost or high-productivity firms will be able to sell abroad a large quantity profitably. Melitz (2003) uses a dynamic industry model with heterogeneous firms to analyze the effect of international trade on the inter-firm reallocation within an industry. Only when firms have observed their productivity, they decide to export. Some firms will produce for the domestic market if their productivity is above some threshold, and export if their productivity is above a higher threshold. Bernard et al. (2003) use a Ricardian model of heterogeneous firms to show that exporters are the most efficient firms producing for the home market and the low cost producers for a foreign market. Extending the idea to foreign direct investment (FDI), Helpman, Melitz and Yeaple (2004) show that in an industry with firms of different levels of productivity, the least productive firms will leave the industry, and the others firms can choose to sell in the domestic market or abroad. However, the high productivity firms will invest in foreign markets and the others will export. Also, in the presence of low trade frictions or economies of scale, exports will be higher than the FDI sales.

In the economic-geography literature the locational characteristics appears as important factors in firms' production and location decisions (Krugman, 1991; Aitken, Hanson and Harrison, 1997). These studies have found that exporters tend to concentrate geographically, giving evidence that geography plays an important role in the export behavior, although few studies have considered such factors in the export decision. Most studies include geographic characteristics using categorical variables such as regional or provincial indicators (Roberts and Tybout, 1997; Bernard and Jensen, 2004b; Limao and Venables, 2001). Several authors (e.g., Venables, 2005) find this simple representation of locational forces inadequate since geography and exports figure prominently in the factors determining spatial income inequality within many developing countries.

4.3 Model

The empirical framework for firms' export behavior in this study is based on the dynamic model with sunk entry/exit costs proposed by Roberts and Tybout (1997). Sunk costs include those on collecting information about foreign markets, creating and maintaining marketing networks, and negotiating and enforcing new contracts (Basile, 2001). Note that many of these costs cannot be recovered if the firm decides to stop selling abroad, i.e., exit costs. Hence, Roberts and Tybout (1997) and Bernard and Jensen (2004a) model the decision to export or continue to export or exit a foreign market as a function of sunk entry/exit costs.

Let $R_i(p, S_i)$ denote revenue from exporting of the *i*-th firm, $i=1,2,\ldots,N$, given prices p and firm-specific factors S_i, including size, productivity, ownership structure and locational factors affecting firm i. At time t, a firm exports, $Y_{it} = 1$, if export revenues exceed costs of production, C_{it}, and any sunk costs of exporting, N:

(1) $$Y_{it} = \begin{cases} 1 & if \;\; R_{it} - C_{it} - N > 0 \\ 0 & otherwise \end{cases} .$$

In order to identify a firm's probability of exporting, equation (1) can be estimated as a binary (discrete) choice using a non-structural approach of the form:

(2) $$Y_{it} = \begin{cases} 1 & if \;\; \beta X_{it} + \gamma Z_{it}^{k} - N + \varepsilon_{it} > 0 \\ 0 & otherwise \end{cases} ,$$

where the vector X_{it} includes the firm-specific characteristics (S_i) and other revenue and cost factors such as employment, wages, R&D intensity and other factors (Bernard and Jensen, 1999; Hanson, 2000). Besides the firm's specific characteristics, geographical factors specific to the k location of the firm, Z_{it}^{k}, are also included.

To account for sunk costs, the linear probabilistic specification of equation (2) is rewritten as:

(3) $$Y_{i,t} = \alpha + \delta Y_{i,t-1} + \beta X_{it} + \gamma Z_{it}^{k} + \varepsilon_{it},$$

where the one-period lagged export decision is used to represent sunk costs (Roberts and Tybout, 1997; Bernard and Jensen, 2004a).

While most earlier studies model export behavior as in equation (3), many do not model the decision on how much to export of the total output, i.e. export intensity (Wagner, 2005). In this study, we augment the export-behavior model with the decision on export intensity as follows:

(4) $$I_{i,t} = \delta + \eta X_{it} + \mu Z_{it}^{k} + \upsilon_{it},$$

where I_{it} is the export intensity of the i-th firm at time t, while X_{it} and Z_{it}^{k} are defined earlier.[1]

4.4 Data

The data used in this study are obtained from the Chilean Annual National Manufacturing Survey (ENIA). Between 1998 to 2003, we track firms through time using the ENIA, and only firms that show export activity in all years are considered. Information is reported at a plant level for those units with more than 20 employees at the regional, provincial and county level.[2] Data includes total sales and export sales (Chilean pesos), structure of ownership (percentage of foreign investors), quantity and/or value of intermediate inputs (materials, electricity, water, and fuel), net capital stock (Chilean pesos), and the structure of employment (number of high/low skill workers). In this study, we consider the two-digit industry 15, the manufacture of food products and beverages, which includes 16 subindustries at the 4-digit level, but only three of the 16 exhibit continued exporting activity. Therefore, only industries 1512 (processing/preserving of fish), 1513 (processing/preserving of fruits and vegetables), and 1552 (wines) are included in the analysis.[3] Among these three, industry 1513 is of special interest given that it is directly related to primary agriculture. Most Chilean fruit farmers do not export directly, but they sell their products to processing industries (mostly included in industry 1513) that export them.

To measure firm-specific productivity included in the vector X_{it} in equations (3) and (4), we use data envelopment analysis (DEA) to obtain an ordering of firms by efficiency scores. Efficiency can be considered as a short-term concept of productivity (Coelli, Rao and Battese, 1998). In particular, we employ an input-output measure of technical efficiency. To implement this efficiency ordering, we require data quantities of inputs and outputs, but for some intermediate inputs and total output we only have (total) value of use and sales. We follow Färe and Grosskopf (1995, 2006) approach to address this problem by assuming that firms face the same prices for inputs and/or outputs. If so, the use of values (cost or sales), instead of the real quantities, will provide the same efficiency scores as those obtained using quantities. Note that the assumption of same prices is made for the industries at the 4-digit level. Thus, the DEA is applied to each of the three 4-digit industries (1512, 1513 and 1552) and years (1998-2003). Formally, the input-oriented measure of technical efficiency (TE) for each decision making unit is specified as:

$$TE_i(q^i, r^i \mid V, S) = \min_{\lambda, z} \lambda$$

$$(5) \quad \begin{aligned} s.t. \quad & q^{im} \leq \sum_{i=1}^{I} z^i q^{im}, && m = 1, \ldots, M, \\ & \sum_{i=1}^{I} z^i r^{in} \leq \lambda r^{in}, && n = 1, \ldots, N, \\ & \sum_{i=1}^{I} z^i = 1; \quad z^i \geq 0 && i = 1, \ldots, I. \end{aligned}$$

where λ is the measure of TE and equals the reciprocal of an input distance function for each firm with output set q^i (total sales) and input set r^i (number of high and low skilled employees, cost of materials, quantity of water, cost of electricity and cost of fuel) under variable returns to scale (V) and strong disposability of inputs (S); z is the intensity vector that permits the construction of the best-practice frontier; I is the number of firms for each 4-digit industry; M is the number of outputs (1); and N is the number of inputs (6). The linear programming problem in equation (5) is solved for each firm. If $\lambda = 1$ the corresponding firm is technically efficient and a value of $\lambda < 1$ indicates that the firm is inefficient.

The role of geography has been considered in the decision to export, but the usual approach includes categorical (dummy) variables associated with regions or zones (Bernard and Jensen, 1995; Roberts and Tybout, 1997; Aitken, Hanson and Harrison, 1997; Limao and Venables, 2001). In this essay, we capture locational forces attracting firms to a particular location (e.g., natural advantages or technical spillovers) using a geographic concentration index (Z_{it}^k). Based on Maurel and Sedillot's (1999) approach, an index that accounts for economic activity in adjacent spatial units, is derived and used in equations (3) and (4).[4] Using this adjacency-effect index, a location-specific geographic concentration indicator is derived. Formally, this variable is defined as $s_i\gamma_j$, where s_i is the employment share of each location, and γ_j the geographic concentration index of each industry *j*. For the purposes of this essay, the geographic concentration index is calculated at the county level. We also consider alternatives to the geographic concentration index in the form of specific variables such as regional human capital, government quality, and infrastructure. Such data are available only at the regional level from *The Regional Competitiveness Report, 2001* (Informe de Competitividad Regional, 2001), published by the Chilean Ministry of Economy (CME). These regional indexes are available for 1997, 1999, 2001 and 2003.

Table 4.1 presents descriptive statistics of the variables used in this essay by industry.[5] Table 4.2 shows descriptive statistics for the pooled observations by market orientation, i.e., traditional and export-oriented firms. Export intensity is calculated as the share of exports in total sales. It gives a standardized representation on the magnitude of firms' exports. Size corresponds to the number of employees of each firm. The high skilled workers variable corresponds to the proportion of those workers in total employment. Foreign ownership is the share of foreign capital in the total capital stock of a plant.[6] All prices were deflated (base year 1992) using a price index from the Chilean Central Bank (2006).

4.5 Econometric Specification

Both the decision to export, equation (3) and the export-intensity decision, equation (4) have contemporaneous firm-specific variables, such as size or high skilled workers on the right hand side. If these regressors are correlated with unobserved firm characteristics (e.g., product attributes or managerial activity) then standard probit or ordinary least squares procedures would produce biased or inconsistent estimates of coefficients in equations (3) and (4). We follow Bernard and Jensen (2004a) who use the one-period lag of explanatory variables to avoid simultaneity and endogeneity issues. Hence, the specification of the export decision and export intensity take the following form:

(6) $$Y_{it} = \alpha + \delta Y_{i,t-1} + \beta X_{i,t-1} + \gamma Z_{it}^{k} + \varepsilon_{it} \;,$$

and:

(7) $$I_{it} = \alpha + \beta X_{i,t-1} + \gamma Z_{it}^{k} + \varepsilon_{itit}^{*} \qquad if\ Y_{it} > 0 \,,$$

where the right-hand-side variables in X_{it} and the dependent variable Y (of equation 6) are lagged one period. The vector Z_{it}^{k} -the geographic attributes- is not lagged, assuming they are exogenous in firms' export decisions.[7]

The dependent variable -the decision to export in equation (6)- is constructed in such a way that it takes the value "0" if export sales are equal to zero or "1" if they are greater than zero. This variable is restricted to the zero-one range, with several observations taking the value zero. A censored (tobit) model is generally used to deal with this situation, wherein all the available information is considered, but the decision to export and the export intensity are jointly modeled. The tobit model assumes that the expected value of the dependent variable depends on the same regressors that explain the export intensity and the decision to export. That is, the tobit model is similar to equation (7), but includes all firms with zeros added whenever a firm did not have recorded export sales. However, zero export activity could reflect two very different decisions: an exporting firm has chosen to produce none for exports or that a firm has decided not to be an exporter. Therefore, the factors influencing the decision to export could be different from those determining the decision on how much to export (export intensity). To deal with this problem, Cragg (1971) proposed a specification in which the two models are contrasted. The first model corresponds to the tobit specification described in the above. The second model includes two stages. In the first stage, the probit model -equation (6)- is used to evaluate the probability of exporting. In the second stage, only the subset of firms that export are considered with the use of truncated-data procedures and observations where the dependent variable takes values greater than zero, i.e., $I_{it} > 0$ in equation (7). The tobit model and the two-stage procedure can be considered as restricted and unrestricted model, respectively. As in Wakelin (1998) and Basile (2001), a choice between the two models can be made using a likelihood ratio (LR) test given by:

(8) $$LR = -2(L_T - L_P - L_{TR})$$

where L_T, L_P, L_{TR}, are the likelihood values from the tobit, probit, and truncated models, respectively. The LR has a chi-squared distribution with degrees of freedom equal to the (highest) number of regressors included in any of the three models.

4.6 Results

Given data availability, the tobit, probit and truncated regressions are estimated for all observations, including the three available years -1999, 2001 and 2003.[8] The primary variable for analyzing the effect of geography in this paper is geographic concentration but, geographic characteristics are included as additional information. The results of the model with geographic characteristics, which are similar to those in tables 4.3 and 4.4, are presented in the appendix.

For all three four-digit industries, the LR test rejected the tobit specification with either geographic concentration (industry 1512, LR = 189.23; industry 1513 LR = 96.08; industry 1552, LR = 73.84) or geographic characteristics (industry 1512, LR = 174.62; industry 1513 LR = 101.39; industry 1552, LR = 70.79). An additional estimation with all observations pooled together also rejected the tobit specification (LR = 355.39 with geographic concentration and LR = 354.31 with geographic characteristics). These results indicate that the decision to export and the export intensity are likely explained by different sets of factors. We therefore focus on the results from probit and truncated regressions with the geographic concentration index in the following sections.

4.7 The Decision to Export

Table 4.3 shows the results of the probit model using the geographic concentration index for all plants pooled together and for each of the three industries, i.e. processing and preserving of fish (1512), processing and preserving of fruits and vegetables (1513), and wines (1552). In all cases, the coefficient on lagged dependent variable, i.e. sunk costs, is positive and significant at the 1% level. This result suggests that a firm will have a higher probability of exporting if it was an exporter in the previous year, which is consistent with that of Roberts and Tybout (1997), Bernard and Jensen (2004a), and others. In other words, if a firm has prior exporting experience (lower sunk costs), its probability of exporting in the current and future periods are higher. In the case of Chilean firms in industries 1512, 1513 and 1552, sunk costs are important determinants of the export decision. In the pooled model, foreign ownership and firm size represented by one-period lagged employment have a positive and significant effect on the export decision. At the industry level, foreign ownership impacts the export decision of industry 1512, at the 1% significance level, and in industry 1513 at the 10% significance level. The lower statistical significance of foreign ownership and size in industry 1513 and 1552 is likely due to the fewer cross sections in those specifications, 37 and 27 respectively (table 4.1). While the result on firm size is consistent with studies reviewed in an earlier section, the effect of foreign ownership on the decision to export appears to have received limited attention. Surprisingly, the variable representing locational forces or attributes, i.e. geographic concentration, does not have a significant effect on the export decision. This does not imply that that geography is not important for exports, but that the binary decision – to export or not – appears not to be impacted by locational forces.[9]

The discussion earlier of the coefficients of the probit model focuses on directionality rather than the relative strength of effects of explanatory variables. To overcome this problem, predicted probabilities of the export decision arising from each significant variable included in equation (6) from table 4.3 are derived. Figure 4.1 plots predicted probabilities due to changes in the sunk-cost indicator (one-period lagged dependent variable) and foreign ownership. For each of these two plots, all other right-hand-side variables are held at their mean. Note the large change in predicted probabilities arising from the sunk-cost indicator relative to that of foreign ownership.[10] These results suggest that larger sunk costs discourage export decision, but lead to greater persistence in export activity. In other words, a firm that makes investments for exporting in a particular year (sunk costs) will have a higher probability of exporting the next year, because it does not need to incur those costs again. On the other hand, a firm that has not exported in the previous year will have to incur (sunk) costs required for exporting if it wishes to export in the current and future periods. Hence, the presence of sunk costs (export inexperience) will reduce the probability of exporting in the current period and future.

4.8 The Export Intensity

Results obtained from the truncated regression model using geographic concentration are presented in table 4.4. The four specifications correspond to a pooled model and three industry-specific models. Among the explanatory variables, foreign ownership alone has a positively and statistically significant coefficient in all four cases, i.e., pooled model and industry 1512, 1513 and 1552. Foreign investors in these industries may have strong links with their respective home countries (marketing and distribution networks), which likely explains this positive relationship. Note that foreign ownership also had a significant and positive effect on the decision to export in three out of four cases (table 4.3). Although foreign ownership is the only variable whose coefficient is significant in the pooled model, the industry-specific models reveal additional insights into the export-intensity decision. Industry 1512 for which we have more cross sections than the other two industries shows that a firm's size and productivity positively affect its export intensity. The result on size provides evidence of economies of scales in export activity, which is consistent with monopolistic competition models of trade (Krugman, 1991). The productivity coefficient is significant at the 10% level. This result is consistent with the self-selection hypothesis noted in the literature review. In the case of industry 1513, the geographic concentration index has a positive and significant effect on the export intensity. Although geographic concentration is not important in firms' decision to export in industry 1513, it appears that the level of exports is influenced by locational forces especially those due to natural advantages. The negative effect of geographic concentration on export intensity in industry 1552 is unexpected, but the corresponding coefficient is only significant at the 10% level.[11]

4.9 Summary and Conclusions

This essay has investigated the role of productivity and geography on the export behavior, i.e., export decision and intensity, of producers in the Chilean food processing industries. Export behavior is derived from firms' dynamic profit maximization with sunk entry or exit costs. A probit model with the one-period lagged dependent variable to represent sunk costs is specified for the decision to export, while a truncated regression framework is employed for modeling export intensity. This two-stage specification allows for different factors to impact behavior at each stage and is found to be statistically preferable to a censored (tobit) model, which combines both decisions into a single dependent variable.

Four specifications of the probit and truncated regression models are estimated: a pooled model and three industry-specific versions, one each for processed fish, fruits/vegetables, and wine industries. In all four models, the decision to export is strongly influenced by sunk costs. That is, firms that have already exported and invested in the extra costs required for such activities appear to have a higher probability of continued exporting. Foreign ownership, represented by percent of capital stock owned by foreigners, positively impacts the export decision. The positive effect of firm size is significant only in the pooled probit model. Geographic concentration does not affect the decision to export in our sample of industries.

The export intensity is also positively influenced by foreign ownership in all industries, which indicates that foreign investors' access to marketing and distribution networks likely increases the scale of exports. Firm size and productivity, and geographic concentration positively affect export intensity in processed fish (1512) and fruits/vegetables (1513) industries, respectively. The latter result indicates a role for locational forces especially natural advantages in the export decision of processed fruits/vegetables industry.

In general, firm-specific characteristics appear to significantly impact export behavior in Chilean processed food industries. The role of geography appears limited in our sample, which mostly included industries that in general had a lower level of spatial concentration of economic activity (essay 1). The dominant role of sunk costs in the export decision calls for further research to explore options to lower such costs to encourage more firms to participate in international trade. For instance, opportunities for firms to work cooperatively to obtain information about new markets can reduce entry costs.

BIBLIOGRAPHY

Aitken, B., G.H. Hanson and A.E. Harrison. 1997. "Spillovers, Foreign Investment and Export Behavior." *Journal of International Economics*, 43(1): 103-132.

Alvarez, R. and R. Lopez. 2004. "Orientacion Exportadora y Productividad en la Industria Manufacturera Chilena." *Cuadernos de Economia* 41(124): 315-343.

Aw, B.Y., S. Chung, and M.J. Roberts. 2000. "Productivity and Turnover in the Export Market: Micro-Level Evidence from the Republic of Korea and Taiwan (China)." *World Bank Economic Review* 14(1): 65-90.

Aw, B.Y., and A. R. Hwang. 1995. "Productivity and the export market: A firm-level analysis." *Journal of Development Economics* 47(2): 313-332.

Basile, R. 2001. "Export Behaviour of Italian Manufacturing Firms over the Nineties: the Role of Innovation". *Research Policy*. 30(8): 1185-1201.

Bernard, A.B. and J. B. Jensen. 1995. "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987." *Brookings Papers on Economic Activity, Microeconomics*. 1995: 67-119.

Bernard, A.B. and J. B. Jensen. 1999. "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* Vol. 47(1): 1-26.

Bernard, A.B., J. Eaton, J. B. Jensen, and S.S. Kortum. 2003. Plants and Productivity in International Trade. *American Economic Review* 93(4): 1268-1290.

Bernard, A.B. and J. B. Jensen. 2004a. "Why Some Firms Export." *Review of Economics and Statistics* 86(2): 561-569.

Bernard, A.B. and J.B. Jensen. 2004b. "Exporting and Productivity in the USA." *Oxford Review of Economic Policy* 20(3): 343-357.

Central Bank of Chile. 2006. External Sector Statistics. www.bcentral.cl .

Clerides, S., S. Lach and J. Tybout. 1998. "Is Learning By Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco." *The Quarterly Journal of Economics* 113(3): 903-947.

Coelli, T.J., D.S.P. Rao, and G.E. Battese. 1998. *An Introduction to Efficiency and Productivity Analysis.* Boston: Kluwer Academic Publishers.

Cragg, J. 1971. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39(3): 829-844.

Delgado, M., J. Farinas, and S. Ruano. 2002. "Firm Productivity and Export Markets: a Non-Parametric Approach." *Journal of International Economics*. 57: 397-422.

Dollar, D. and A. Kraay. 2004. "Trade, Growth, and Poverty." *The Economic Journal* 114(493): F22-F49.

Easterly W. 2004. "Globalization, Poverty, and All That: Factor Endowment versus Productivity Views." NBER Globalization Workshop, September.

Färe, R. and S. Grosskopf. 1995. "A Nonparametric Cost Approach to Scale Efficiency". *Scandinavian Journal of Economics*. 87(4): 594-604.

Färe, R. and S. Grosskopf. 2006."Resolving a Strange Case of Efficiency". *Journal of the Operational Research Society*, in press.

Frankel, J. and D. Romer. 1999. "Does trade cause growth?" *American Economic Review* 89: 379-399.

Giles, J.A., and C.L. Williams. 2000. "Export-led growth: a survey of the empirical literature and some non-causality results." Part I. *Journal of International Trade & Economic Development* 9(3):261-337.

Girma, S., D. Greenaway, and R. Kneller. 2004. "Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms." *Review of International Economics* 12(5): 855-66.

Hanson, G.H. 2000. "Scale Economies and the Geographic Concentration of Industry." NBER Working Paper No. 8013, Cambridge, MA.

Helpman, E., M. Melitz and S. Yeaple. 2004. "Export Versus FDI with Heterogeneous Firms." *American Economic Review* 94(1): 300-316.

Krugman, P, 1991. *Geography and Trade*. Cambridge, MA: MIT Press.

Limao, N. and A.J. Venables. 2001. "Infrastructure, Geographical Disadvantage and Transport Costs." *World Bank Economic Review* 15(3): 451-479.

Long, J. S. 1997. Regression Models for Categorical and Limited Dependent Variables. Advanced Quantitative Techniques in the Social Sciences Series 7. Sage Publications, Inc. Thousand Oaks, CA.

Maurel, F. and B. Sedillot. 1999. "A Measure of the Geographical Concentration in French Manufacturing Industries." *Regional Science and Urban Economics* 29: 575-604.

Melitz, M. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica* 71(6): 1695-1725.

Roberts, M. and J. Tybout. 1997. “The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs.” *American Economic Review*, 87(4):545-564.

Venables A. J. 2005. “Spatial disparities in developing countries: cities, regions, and international trade.” *Journal of Economic Geography* 5(1): 3-21.

Wagner, J. 2005. “Exports and Productivity: A survey of the Evidence from Firm Level Data.” University of Lüneburg, Working Paper 4.

Wakelin, K. 1998. “Innovation and Export Behaviour at the Firm Level”. *Research Policy*. 26(7-8): 829-841.

Yeaple, S. 2005. “A simple model of Firm Heterogeneity, International Trade, and Wages”. *Journal of International Economics* 65(1): 1-20.

Table 4.1. Descriptive Statistics on Firm-Specific Characteristics and Geographic Concentration by Industries

	Mean	Standard Deviation	Minimum	Maximum
Industry 1512 (76 plants)				
Decision to Export	0.7265	0.4467	0	1
Export Intensity	0.5302	0.3765	0	1
Productivity	0.7803	0.2354	0.26	1
Size (Number of Employees)	203.0342	263.8005	9	1581
High Skilled Workers (Share)	0.2482	0.2854	0	1
Foreign Ownership	0.1249	0.3184	0	1
Geographic Concentration	0.0038	0.0034	0	0.01
Industry 1513 (37 plants)				
Decision to Export	0.6091	0.4902	0	1
Export Intensity	0.3548	0.3721	0	1
Productivity	0.7394	0.2571	0.24	1
Size (Number of Employees)	168.7091	208.4997	8	1046
High Skilled Workers (Share)	0.2493	0.2534	0.04	1
Foreign Ownership	0.0981	0.2866	0	1
Geographic Concentration	0.0014	0.0022	0	0.01051
Industry 1552 (27 plants)				
Decision to Export	0.7439	0.4392	0	1
Export Intensity	0.4170	0.3747	0	1
Productivity	0.8349	0.2131	0.36	1
Size (Number of Employees)	145.0244	209.9834	11	1089
High Skilled Workers (Share)	0.3367	0.2351	0.0222	1
Foreign Ownership	0.0318	0.1112	0	0.57
Geographic Concentration	0.0017	0.0022	0.000029	0.01051

Table 4.2. Descriptive Statistics on Firm-Specific Characteristics and Geographic Concentration of Pooled Observations by Market Orientation

	Mean	Standard Deviation	Minimum	Maximum
Traditional Oriented Farms (40 firms)				
Decision to Export	0.0000	0.0000	0	0
Export Intensity	0.0566	0.1939	0	0.98
Productivity	0.8093	0.2330	0.24	1
Size (Number of Employees)	67.0469	70.4800	8	336
High Skilled Workers (Share)	0.2488	0.2783	0	1
Foreign Ownership	0.0326	0.1742	0	1
Geographic Concentration	0.0023	0.0031	0	0.0105095
Export Oriented Farms (100 firms)				
Decision to Export	1.0000	0.0000	1	1
Export Intensity	0.6378	0.3014	0	1
Productivity	0.7678	0.2406	0.25	1
Size (Number of Employees)	232.8121	270.1042	10	1581
High Skilled Workers (Share)	0.2727	0.2664	0	1
Foreign Ownership	0.1291	0.3147	0	1
Geographic Concentration	0.0030	0.0031	0	0.0105095

Table 4.3. The Probit Model with Geographic Concentration

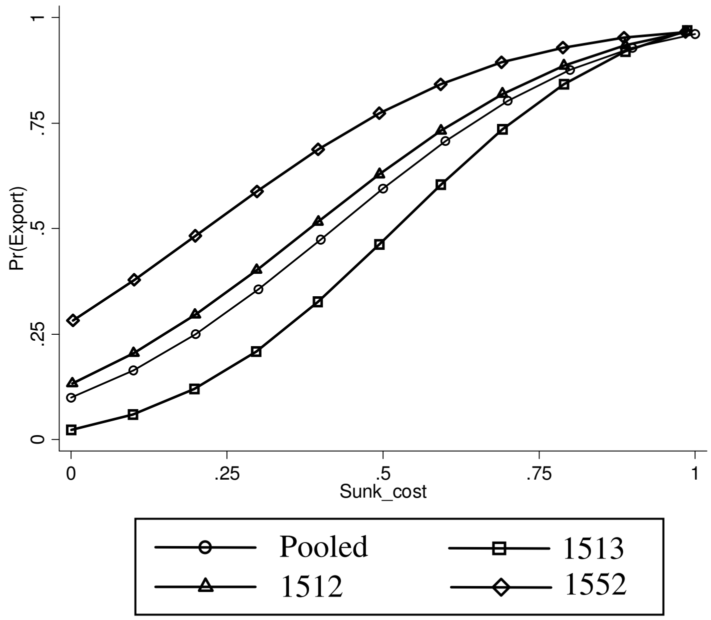
	Pooled	Industry 1512	Industry 1513	Industry 1552
Exported Last Year	3.055***	3.081 ***	3.458 ***	2.772 ***
	(0.257)	(0.397)	(0.556)	(0.526)
Productivity	-0.420	0.081	-1.202	-0.584
	(0.442)	(0.605)	(0.850)	(1.142)
Foreign Ownership	1.229***	1.465 ***	1.205 *	-0.606
	(0.372)	(0.601)	(0.663)	(2.939)
Size	0.002**	0.002	0.001	0.003
	(0.001)	(0.001)	(0.001)	(0.005)
High Skilled Workers	0.035	0.327	-0.571	0.082
	(0.348)	(0.460)	(0.965)	(0.759)
Geographic Concentration	41.078	42.489	21.258	-44.974
	(36.842)	(53.006)	(165.797)	(80.710)
Intercept	-0.742	-2.212 ***	-1.118	-0.511
	(0.482)	(0.657)	(0.729)	(0.959)
Industry Dummies	Yes			
Number of observations	420	228	111	81
Wald chi-squared ([1])	169.04	77.19	43.89	45.76
Log-likelihood value	-83.01	-46.47	-18.17	-16.58
Pseudo R^2	0.6707	0.6427	0.7532	0.6313

Numbers in parentheses are standard errors.
* significant at 10%.
** significant at 5%.
*** significant at 1%.
[1] 8, 6, 6, and 6 degrees of freedom, respectively.

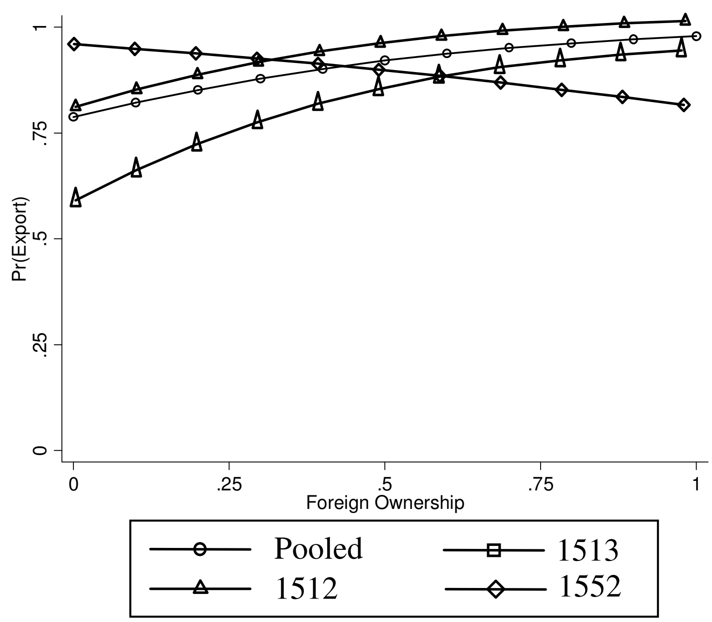
Table 4.4. Truncated Regression Model with Geographic Concentration

	Pooled	Industry 1512	Industry 1513	Industry 1552
Productivity	0.013	0.158 *	-0.211	0.024
	(0.079)	(0.091)	(0.186)	(0.240)
Foreign Ownership	0.248***	0.146 ***	0.493 ***	0.515 ***
	(0.046)	(0.055)	(0.098)	(0.204)
Size	0.000	0.000 **	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
High Skilled Workers	0.022	0.015	0.140	0.020
	(0.066)	(0.063)	(0.237)	(0.224)
Geographic Concentration	0.047	-5.606	89.959 ***	-81.694 *
	(5.860)	(6.190)	(28.871)	(45.070)
Intercept	0.556***	0.528 ***	0.492 ***	0.642 ***
	(0.080)	(0.077)	(0.156)	(0.212)
Industry Dummies	Yes			
Number of observations	302	176	70	56
Wald chi-squared ([1])	44.02	16.57	32.20	16.98
Log-likelihood value	-37.46	-10.70	-6.04	-6.78

Numbers in parentheses are standard errors.
* significant at 10%.
** significant at 5%.
*** significant at 1%.
[1] 7, 5, 5, and 5 degrees of freedom, respectively.



Panel (a): Sunk-Cost Indicator



Panel (b): Foreign Ownership

Figure 4.1: Predicted Probabilities Due to Changes in Sunk-Cost Indicator and Foreign Ownership

APPENDICES

Appendix 4.1: Descriptive Statistics of Geographic Characteristics by Region

	Region	Mean	Standard Deviation	Minimum	Maximum
Human Capital	1	0.55	0.01	0.53	0.56
	2	0.63	0.02	0.61	0.66
	3	0.46	0.04	0.42	0.49
	4	0.41	0.04	0.35	0.46
	5	0.60	0.01	0.59	0.62
	6	0.33	0.03	0.31	0.37
	7	0.35	0.03	0.31	0.37
	8	0.40	0.04	0.36	0.45
	9	0.30	0.05	0.24	0.35
	10	0.33	0.03	0.30	0.36
	11	0.44	0.03	0.42	0.48
	12	0.62	0.04	0.58	0.67
	13	0.71	0.03	0.67	0.74
Government Quality	1	0.27	0.08	0.19	0.38
	2	0.28	0.04	0.25	0.33
	3	0.48	0.08	0.41	0.57
	4	0.47	0.08	0.40	0.58
	5	0.30	0.02	0.29	0.32
	6	0.40	0.05	0.34	0.46
	7	0.39	0.10	0.28	0.51
	8	0.47	0.01	0.46	0.49
	9	0.37	0.19	0.17	0.54
	10	0.48	0.09	0.38	0.59
	11	0.76	0.13	0.60	0.91
	12	0.39	0.14	0.24	0.56
	13	0.39	0.05	0.32	0.43
Infrastructure	1	0.24	0.04	0.21	0.28
	2	0.27	0.03	0.25	0.30
	3	0.08	0.01	0.07	0.09
	4	0.12	0.03	0.09	0.15
	5	0.23	0.00	0.23	0.24
	6	0.07	0.01	0.06	0.09
	7	0.02	0.02	0.00	0.04
	8	0.09	0.01	0.08	0.09
	9	0.05	0.02	0.02	0.06
	10	0.07	0.02	0.05	0.09
	11	0.05	0.01	0.04	0.06
	12	0.27	0.03	0.23	0.31
	13	0.40	0.00	0.39	0.40

Appendix 4.2: The Probit Model with Geographic Characteristics

	Pooled	Industry 1512	Industry 1513	Industry 1552
Exported Last Year	3.073***	2.866 ***	4.644 ***	2.827 ***
	(0.270)	(0.415)	(0.844)	(0.559)
Productivity	-0.450	-0.078	-1.646	-0.818
	(0.437)	(0.569)	(1.360)	(1.231)
Foreign Ownership	1.160***	1.361 ***	1.369 **	-0.403
	(0.343)	(0.550)	(0.602)	(2.357)
Size	0.002***	0.003 **	0.002 ***	0.003
	(0.001)	(0.001)	(0.001)	(0.003)
High Skilled Workers	0.083	0.511	-0.533	0.137
	(0.353)	(0.477)	(0.944)	(0.717)
Human Capital	-2.358	-0.722	-16.577 ***	0.783
	(2.307)	(2.986)	(3.510)	(5.153)
Government Quality	-0.277	0.839	-6.113 **	0.522
	(0.857)	(1.117)	(2.782)	(2.619)
Infrastructure	2.521	3.454	16.419 ***	-2.024
	(2.685)	(3.658)	(4.162)	(6.311)
Intercept	0.123	-2.457 ***	5.915 ***	-0.666
	(0.786)	(0.973)	(1.845)	(1.487)
Industry Dummies	Yes			
Number of observations	420	228	111	81
Wald chi-squared ([1])	188.88	96.86	68.15	47.43
Log-likelihood value	-82.93	-45.94	-14.86	-16.30
Pseudo R^2	0.6710	0.6467	0.7981	0.6376

Numbers in parentheses are standard errors.
* significant at 10%.
** significant at 5%.
*** significant at 1%.
[1] 10, 8, 8, and 8 degrees of freedom, respectively.

Appendix 4.3: Truncated Regression Model with Geographic Characteristics

	Pooled	Industry 1512	Industry 1513	Industry 1552
Productivity	0.013	0.153 *	-0.279	-0.109
	(0.079)	(0.090)	(0.226)	(0.270)
Foreign Ownership	0.245***	0.126 **	0.413 ***	0.538 **
	(0.047)	(0.057)	(0.104)	(0.264)
Size	0.000	0.000	0.000	0.000 *
	(0.000)	(0.000)	(0.000)	(0.000)
High Skilled Workers	0.024	0.010	0.163	0.061
	(0.066)	(0.064)	(0.259)	(0.226)
Human Capital	-0.472	-0.474	0.365	-0.502
	(0.334)	(0.335)	(1.138)	(1.367)
Government Quality	0.113	0.320 *	-0.812	0.051
	(0.148)	(0.168)	(0.648)	(0.785)
Infrastructure	0.496	0.690	-0.845	0.763
	(0.399)	(0.443)	(1.286)	(1.500)
Intercept	0.655***	0.489 ***	0.975 **	0.784 *
	(0.135)	(0.141)	(0.418)	(0.424)
Industry Dummies	Yes			
Number of observations	302	176	70	56
Wald chi-squared ([1])	47.57	22.59	24.61	8.86
Log-likelihood value	-36.34	-8.81	-7.33	-7.95

Numbers in parentheses are standard errors.
* significant at 10%.
** significant at 5%.
*** significant at 1%.
[1] 9, 7, 7, and 7 degrees of freedom, respectively.

ENDNOTES

[1]Sunk costs are not considered in the export intensity equation.

[2]Decisions at a firm level could differ from those at a plant level, but in this study we treat them as synonymous.

[3]The focus on exporting industries is not unique to this study. See Bernard and Jensen (1995) and Roberts and Tybout (1997).

[4]A detailed explanation of this index is provided in the first essay "*Geographic Concentration of the Chilean Manufacturing Industry.*"

[5]Only observations form 1999, 2001 and 2003 are presented in these statistics because only these years will be used in the analysis, as it will be explained later.

[6]Some variables are normalized to avoid convergence problems in tobit and probit models. Long (1997) recommends that the ratio of the maximum and minimum of a variable should not exceed 10.

[7]Using lags of the geographic variables would lead to dropping the data from 1999.

[8]When the lagged dependent variable was included in the tobit model, we had difficulty obtaining convergence and so, we dropped this variable from its specification. When sunk costs are dropped from all specifications (tobit, probit and truncated regression), the likelihood ratio test results do not change from that reported here. Hence, it is unlikely that dropping them from the tobit model would affect the results of the LR test. An alternative estimation without the lagged variable in the probit specification alone also rejected the tobit model in favor of the joint use of the other two models.

[9]The probit model that uses geographic characteristics is reported in appendix 4.2 for all plants pooled together and for the three food processing industries. Sunk costs are again important for the three industries' export decision as evidenced by the positive and statistically significant coefficients on one-period lagged exports. Foreign ownership and size are positively associated with the export decision of industry 1512 and 1513 at the 5% significance level. Geographic characteristics do not impact the (binary) decision to export of industries 1512 and 1552, but show mixed results for industry 1513. In this industry, human capital and government quality have a significant and negative sign, but infrastructure has a significant positive effect.

[10]Although not shown, the predicted probabilities due to changes in firm size (pooled model, table 4.3) also show a pattern similar to that of foreign ownership.

[11]Appendix 4.3 reports the truncated regression results when geographic characteristics are included. The role of foreign ownership continues to be relevant for all industries. Positive effects appear for productivity in industry 1512 and size in industry 1552, but only at the 10% significance level. Evidence of the effect of geographic characteristics on the export intensity is limited: government quality is positive in industry 1512, but only at the 10% significance level.

CHAPTER FIVE

CONCLUSION

This dissertation, composed of three essays, has analyzed the relative importance of firm-specific and geographic characteristics to firms' export behavior in the Chilean primary and processed food industries. Geographic characteristics are represented using traditional indicators and indexes of spatial concentration of economic activity developed in essay 1. In general, results show that firm-specific characteristics are more important than geographical attributes in the export decision of Chilean firms.

In chapter two (essay 1), the geographic concentration of the Chilean manufacturing industry is analyzed. A new index of geographic attributes is developed so as to account for concentration of economic activity in adjacent, but separate spatial units. This index reflects the geographic characteristics that are relevant to specific industries, and also, provides a ranking of spatial units based on the degree of concentration. Previous indexes of geographic concentration and the new one developed in this essay are applied to the Chilean case. The new index captures a higher degree of geographic concentration relative to previous indexes due to the former's accounting of adjacent economic activity. Moreover, it appears that higher geographic concentration of the Chilean manufacturing industry is led by technological spillovers in highly populated areas, and the access to natural resources in areas that are farther from big markets.

Chapter three (essay 2) analyzes the relative importance of farm-specific and geographic characteristics in the Chilean farms' decision to producer exportables, i.e., export participation. To achieve this objective, an export behavior model is estimated using data on 8,284 Chilean farms and a two-stage conditional maximum likelihood procedure. Results suggest that a farm's efficiency has a relatively stronger effect than geography on its export participation. This result is consistent with that found in the context of manufacturing firms. When a highly productive farm locates in a region with better geographic characteristics, its likelihood of producing for export markets is higher. On the other hand, an opposite result is obtained when a low-productivity farm locates in regions with better geographic attributes. Farms with skilled (managerial) labor also have a relatively higher probability of producing for the export market. The above results suggest that farms must achieve a minimum level of efficiency for geographic characteristics to positively affect their export participation.

In chapter four (essay 3), the decision to export as well as that on export intensity are investigated. Here a sequencing by way of a two-stage procedure, the decision to export followed by that on export intensity, is well supported by data. Moreover, the two stages appear to have different explanatory factors. In the export-decision stage, sunk cost is a key determinant of a firm's export probability. Foreign ownership and firm size also have positive effects on the export decision. In selected industries, productivity and geography play a more prominent role in the decision on export intensity, which is also positively impacted by foreign ownership. In general, firm-specific characteristics appear to be more important than geographic attributes in firms' export behavior.

In summary, these essayss have improved the knowledge on export behavior of firms, in general, and in the Chilean agriculture and processed food industries. The essays provide insights into factors determining export behavior, with implications for the focus or thrust of government policies to encourage export activity in these segments of the Chilean economy. Future research should focus on evaluating alternative policies to positively impact factors encouraging export participation and their welfare implications for agriculture, processed food industries and the overall Chilean economy.

BIBLIOGRAPHY

Agosin, M. 1999. "Trade and Growth in Chile". *CEPAL Review* 68: 79-100.

Aitken, B., G.H. Hanson and A.E. Harrison. 1997. "Spillovers, Foreign Investment and Export Behavior." *Journal of International Economics*, 43(1): 103-132.

Aksoy, A.M., and J.C. Beghin. 2005. *Global Agricultural Trade and Developing Countries*. Washington DC: The World Bank Press.

Alonso-Villar O, J.M. Chamorro-Rivas, and X. Gonzalez-Cerdeira. 2004. "Agglomeration Economies in Manufacturing Industries: the Case of Spain". *Applied Economics* 36(18): 2103-2116.

Alvarez, R. and R. Lopez. 2004. "Orientacion Exportadora y Productividad en la Industria Manufacturera Chilena." *Cuadernos de Economia* 41(124): 315-343.

Avendaño, O. 2001. "Diferenciacion y Conflicto en el Empresariado Agricola Chileno. Periodo 1975-1998". Debates y Reflexiones. Aportes para la Investigacion Social. Universidad de Chile, Programa de Estudios Desarrollo y Sociedad. Document No 3.

Aw, B.Y., and A. R. Hwang. 1995. "Productivity and the export market: A firm-level analysis." *Journal of Development Economics* 47(2): 313-332.

Aw, B.Y., S. Chung, and M.J. Roberts. 2000. "Productivity and Turnover in the Export Market: Micro-Level Evidence from the Republic of Korea and Taiwan (China)." *World Bank Economic Review* 14(1): 65-90.

Basile, R. 2001. "Export Behaviour of Italian Manufacturing Firms over the Nineties: the Role of Innovation". *Research Policy*. 30(8): 1185-1201.

Bernard, A.B. and J. B. Jensen. 1995. "Exporters, Jobs, and Wages in U.S. Manufacturing: 1976-1987." *Brookings Papers on Economic Activity, Microeconomics*. 1995: 67-119.

Bernard, A.B. and J. B. Jensen. 1997. "Exporters, Skill Upgrading and the Wage Gap" *Journal of International Economics* Vol. 42(3): 3-31.

Bernard, A.B. and J. B. Jensen. 1999. "Exceptional Exporter Performance: Cause, Effect, or Both?" *Journal of International Economics* Vol. 47(1): 1-26.

Bernard, A.B. and J. B. Jensen. 2004a. "Why Some Firms Export." *Review of Economics and Statistics* 86(2): 561-569.

Bernard, A.B. and J.B. Jensen. 2004b. "Exporting and Productivity in the USA." *Oxford Review of Economic Policy* 20(3): 343-357.

Bernard, A.B., J. Eaton, J. B. Jensen, and S.S. Kortum. 2003. Plants and Productivity in International Trade. *American Economic Review* 93(4): 1268-1290.

Braunerhjelm, P. and B. Borgman. 2004. "Geographical Concentration, Entrepreneurship and Regional Growth: Evidence from Regional Data in Sweden, 1975-99." *Regional Studies* 38 (8): 929-947.

Central Bank of Chile. 2006. External Sector Statistics. www.bcentral.cl .

Clerides, S., S. Lach and J. Tybout. 1998. "Is Learning By Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco." *The Quarterly Journal of Economics* 113(3): 903-947.

Coelli, T.J., D.S.P. Rao, and G.E. Battese. 1998. *An Introduction to Efficiency and Productivity Analysis.* Boston: Kluwer Academic Publishers.

Cohen, J.P., and C.J. Morrison Paul. 2004. "Public Infrastructure Investment, Interstate Spatial Spillovers and Manufacturing Costs." *Review of Economics and Statistics* 86(2):551-560.

Coughlin C. and P. Pollard. 2001. "Comparing Manufacturing Export Growth across States: What Accounts for the Differences? *Federal Reserve Bank of St. Louis*.

Cragg, J. 1971. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." *Econometrica* 39(3): 829-844.

Delgado, M., J. Farinas, and S. Ruano. 2002. "Firm Productivity and Export Markets: a Non-Parametric Approach." *Journal of International Economics*. 57: 397-422.

Devereux M., R. Griffith, and H. Simpson. 2004. "The Geographic Distribution of Production Activity in the U.K.". *Regional Science and Urban Economics* 34 (5): 533-564.

Dixit, A.K., and J.E. Stiglitz. 1977. "Monopolistic Competition and Optimum Product Diversity." *The American Economic Review* 67(3): 297-308.

Dollar, D. and A. Kraay. 2004. "Trade, Growth, and Poverty." *The Economic Journal* 114(493): F22-F49.

Duranton, G. and H. Overman. 2005. "Testing for localization using micro-geographic data." *Review of Economic Studies* 72, 1077-1106.

Easterly W. 2004. “Globalization, Poverty, and All That: Factor Endowment versus Productivity Views.” NBER Globalization Workshop, September.

Ellison G. and E. Glaeser. 1994. “Geographic Concentration in US Manufacturing Industries: A Dartboard Approach.” Working Paper No 3840 NBER.

Ellison G. and E. Glaeser. 1997. “Geographic Concentration in US Manufacturing Industries: A Dartboard Approach.” *Journal of Political Economy* 105(5): 889-927.

Färe, R. and S. Grosskopf. 1995. “A Nonparametric Cost Approach to Scale Efficiency”. *Scandinavian Journal of Economics*. 87(4): 594-604.

Färe, R. and S. Grosskopf. 2006.“Resolving a Strange Case of Efficiency”. *Journal of the Operational Research Society*, in press.

Frankel, J. and D. Romer. 1999. “Does trade cause growth?” *American Economic Review* 89: 379-399.

Fujita M. and J. Thisse. 2002. *Economics of Agglomeration: Cities, Industrial Location and Regional Growth.* Cambridge: Cambridge University Press.

Fujita M. and J. Thisse. 2003. “Does Geographical Agglomeration Foster Economic Growth? And Who Gains and Loses from It?.” *The Japanese Economic Review* 54(2): 121-145.

Fujita M. and T. Mori. 2005. “Frontiers of the New Economic Geography.” *Papers in Regional Science*. 84(3): 377-405.

Fujita M., P. Krugman, and A. Venables. 1999. *The Spatial Economy. Cities, Regions and International Trade.* Cambridge: MIT Press.

Giles, J.A. and C.L. Williams. 2000. “Export-led growth: a survey of the empirical literature and some non-causality results.” Part I. *Journal of International Trade and Economic Development* 9(3): 261-337.

Girma, S., D. Greenaway, and R. Kneller. 2004. “Does Exporting Increase Productivity? A Microeconometric Analysis of Matched Firms.” *Review of International Economics* 12(5): 855-66.

Hanson, G.H. 2000. “Scale Economies and the Geographic Concentration of Industry.” NBER Working Paper No. 8013, Cambridge, MA.

Helpman, E., M. Melitz and S. Yeaple. 2004. “Export Versus FDI with Heterogeneous Firms.” *American Economic Review* 94(1): 300-316.

Krugman, P. 1980. “Scale Economies, Product Differentiation, and the Pattern of Trade.” *The American Economic Review* 70(5): 950-959.

Krugman, P. 1991a. Geography and Trade, MIT Press, Cambridge, MA.

Krugman, P. 1991b. “Increasing Returns and Economic Geography”. *Journal of Political Economy* 99(3): 483:499.

Krugman, P. 1998. “Space: The Final Frontier”. *Journal of Economics Perspectives* 12(2): 161:174.

Krugman, P., and A. Venables. 1995. “The Seamless World: A Spatial Model of International Specialization.” Working Paper No 5220 NBER.

Krugman, P. 1999. “The Role of Geography in Development”. *International Regional Science Review* 22(2): 142:161.

Limao, N. and A.J. Venables. 2001. “Infrastructure, Geographical Disadvantage and Transport Costs.” *World Bank Economic Review* 15(3): 451-479.

Long, J. S. 1997. Regression Models for Categorical and Limited Dependent Variables. Advanced Quantitative Techniques in the Social Sciences Series 7. Sage Publications, Inc. Thousand Oaks, CA.

Marcon, E. and F. Puech, 2003. Evaluating the geographic concentration of industries using distance-based methods. Journal of Economic Geography 3, 409-428.

Martin, P. and G. Ottaviano. 2001. “Growth and Agglomeration.” *International Economic Review* 42(4): 947-968.

Maurel, F. and B. Sedillot. 1999. “A Measure of the Geographical Concentration in French Manufacturing Industries.” *Regional Science and Urban Economics* 29: 575-604.

Melitz, M. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity.” *Econometrica* 71(6): 1695-1725.

ODEPA, 2001. *Compendio Estadístico Silvoagropecuario* 1990-2000.

Pavcnik, N. 2002 “Trade Liberalization, Exit, and Productivity Improvement: Evidence from Chilean Plants.” *Review of Economic Studies* 69(1): 245-76.

Portilla, B. 2000. “La Política Agrícola en Chile: Lecciones de Tres Décadas.” Serie Desarrollo Productivo 68. Economic Commission for Latin America and the

Caribbean.

Redding S. and A.J. Venables. 2003. "Geography and Export Performance: External Market Access and Internal Supply Capacity." Working Paper, 9637, National Bureau of Economic Research, Cambridge, MA.

Richardson, J.D. and K. Rindal. 1995. Why Exports Really Matter! The Institute for International Economics, Washington DC.

Rivers, D. and Q. Vuong. 1988. "Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models." *Journal of Econometrics*, 39(3):347-366.

Roberts, M. and J. Tybout. 1997. The Decision to Export in Colombia: An Empirical Model of Entry with Sunk Costs. *American Economic Review*, 87(4):545-564.

Saéz. S. and J.G. Valdés. 1999. "Chile and its Lateral Trade Policy". CEPAL Review 67. Economic Commission for Latin America and the Caribbean.

Suelos. El Principio de la Vid. 2001. Vendimia. 2001. 3(20).

Venables, A. 1996. "Equilibrium Locations of Vertically Linked Industries." *International Economic Review* 37(2): 341-359.

Venables A. 2005. "Spatial disparities in developing countries: cities, regions, and international trade." *Journal of Economic Geography* 5(1): 3-21.

Venables, A., and N. Limao. 2002. "Geographical Disadvantage: A Heckscher-Ohlin-von Thunen model of International Specialization". Journal of International Economics 58(2): 239-263.

Wagner, J. 2005. "Exports and Productivity: A survey of the Evidence from Firm Level Data." University of Lüneburg, Working Paper 4.

Wakelin, K. 1998. "Innovation and Export Behaviour at the Firm Level". *Research Policy*. 26(7-8): 829-841.

Wooldridge, J. M., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.

World Bank. 2001. "Chile: Poverty and Income Distribution in a High-Growth Economy 1987-1998." Report No. 22037-CH, August 30, Washington D.C.

Yeaple, S. 2005. "A simple model of Firm Heterogeneity, International Trade, and Wages". *Journal of International Economics* 65(1): 1-20.