Vertical industry relations, spillovers and productivity: Evidence from Chilean plants

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Abstract

We use disaggregated data on Chilean plants, and the Chilean input-output table to examine the impact of agglomeration spillovers on total factor productivity (TFP). In common with previous studies, we find evidence of intra-industry spillovers, but no evidence of cross-industry spillovers in general. This picture changes, however, when we take vertical industry relations into account. We find important productivity spillover effects from plants in upstream industries. Interestingly, a similar effect cannot be found from plants in downstream industries. The number of plants in these sectors has no effect on firm level TFP, just as the number of plants in other industries that are neither important upstream suppliers nor downstream customers also has no effect. Agglomeration effects are stronger for small than for large plants.

October 2008

Keywords: Vertical linkages, agglomeration, productivity, Chile

JEL class.: R11, R15, O18, O54

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The authors thank Gerhard Glomm, Kim Huynh, Andrea Lamorghese, Will Strange, and seminar participants at the NARSC annual meetings at Savannah (GA) for helpful comments and discussions. The usual disclaimer applies. Parts of this paper were written while Südekum was visiting Indiana University Bloomington. We acknowledge the hospitality of this institution. This work was supported by a grant from the Ministry of Science, Research and the Arts of Baden-Württemberg (Az: 21-655.042-5-2/1) to Jens Südekum.

1. Introduction

In his seminal work, Marshall (1920) described three different reasons for why economic activity tends to agglomerate in space. In new jargon, his theories are now usually labeled (1) knowledge spillovers, (2) labor pooling and (3) input-output linkages between vertically related industries. A large theoretical literature has been developed that provides formal models of these and other theories of agglomeration. It is furthermore well documented by now that a high density of economic activity (e.g., in cities) increases productivity. Ciccone and Hall (1996) and Ciccone (2002) have shown this for the US and for Europe, respectively. For empirical research, however, the principal challenge remains that the various theories of agglomeration often lead to observationally equivalent outcomes, so that it is difficult to disentangle the (relative) empirical relevance of different agglomeration forces (Rosenthal and Strange 2004).[1]

An important step forward has been made by Henderson (2003), who uses plant-level productivity data to address the nature of agglomeration forces. The use of such data has several advantages over the more traditional approach based on aggregate data for regions or local industries. Firstly, a variety of firm characteristics (such as size or age) can be controlled for, which are hidden in aggregate figures but which must be sharply distinguished from Marshallian externalities.[2] Furthermore, if the data allows following single firms over time, one can control for unobserved heterogeneity in order to address endogenous spatial sorting. This issue has turned out to be crucial in the empirical agglomeration literature (see e.g. Gould 2007, Combes et al., 2008): Does the concentration of economic activity really cause productivity gains, or do more productive agents (firms or, respectively, workers) self-select into particular regions so that the measured agglomeration effects are biased upwards?

Henderson (2003) argues that localization effects are strongly pervasive. A firm that is located in a region specialized in the firm's sector of activity is found to be significantly more productive than an isolated firm in a region where the respective

[1] Duranton and Puga (2004) suggest a slightly different terminology of agglomeration forces than Marshall: sharing, matching, and learning. They provide an excellent overview of the different theories of agglomeration. In the same edited volume, Rosenthal and Strange (2004) describe the current state of art in the empirical literature on agglomeration.

[2] We use the terms 'plant' and 'firm' interchangeably in this paper. For the case of Chile, the majority of firms are actually single plants.

industry is underrepresented. No evidence is found for urbanization forces. Plant-level productivity does not seem to depend on spillovers from other industries or, more generally, on the diversity of the surrounding local economic structure. These findings have been corroborated by Cingano and Schivardi (2003) and Mayer et al. (2008) for Italy and for France, respectively. These studies also rely on disaggregate productivity data and find a striking dominance of localization effects but no evidence for urbanization effects.[3]

The picture that emerges from these studies is consistent with some theories of agglomeration, in particular with intra-industry knowledge spillovers. It is not easily reconciled, however, with other agglomeration theories that rely on input-output relations or on cross-industry effects between vertically related sectors. Furthermore, the complete absence of cross-industry spillovers found in these studies is quite puzzling, given that several other empirical papers that adopt a more aggregate approach do in fact emphasize the relevance of such effects for understanding the phenomenon of agglomeration.

A starting point in that respect is the paper by Holmes (1999) who reports a positive correlation between the degree of localization of an industry and its "purchased input intensity", i.e., its degree of vertical dis-aggregation. Firms rely more heavily on outsourcing in specialized environments than in isolation, which suggests that input-output linkages are important for spatial concentration. But since his work uses cross-section data of local industries, the direction of the causality and the implications of vertical dis-aggregation for individual firm productivity remain unclear. Similarly, Rigby and Essletzbichler (2002) find that average labor productivity is higher in metropolitan areas with a large density of input-output relations, while Rosenthal and Strange (2001) find a higher degree of localization in industries that rely more intensively on manufacturing inputs. Finally, Ellison et al. (2007) draw on the co-agglomeration index developed in Ellison and Glaeser (1997) and find stronger co-location among industries that have closer input-output relations. Common to these contributions is thus the

[3] These studies find their roots in the older literature on localization vs. urbanization (sometimes also called Marshall-Arrow-Romer vs. Jacobs externalities), which has been pioneered by Glaeser et al. (1992) and Henderson et al. (1995). That literature has traditionally relied on aggregate data and addressed the impact of local economic structures on employment growth of local industries. Henderson (2003) has been the first to extend this literature to plant-level productivity studies.

conclusion that vertical linkages are important agglomeration forces. Yet, since these studies are based on aggregate data, their results have to taken cautiously.

The main aim of this study is to unify these different strings in the empirical agglomeration literature. We use an extensive data set that covers the universe of Chilean manufacturing plants from 1990 to 1999, and that entails detailed information about the firms' inputs. Furthermore, we use the Chilean input-output matrix to account for vertical relationships between different industries. We first estimate total factor productivity (TFP) at the plant level, and then use this measure as the dependent variable in a panel analysis where we control for the number of plants in different industries, several plant characteristics as well as several types of fixed effects. With these variables we capture important externalities that may be internal to an industry or extend across industries.

In common with Henderson (2003) we find significantly positive intra-industry spillover effects but no evidence for general cross-industry effects or urbanization forces: Plant-level productivity is not affected by the presence of firms from other industries. This picture changes, however, when we take vertical relations into account. We find that productivity of a firm is higher the more plants from important upstream sectors are located in the same region. Put differently, there are no ubiquitous cross-industry effects between firms from arbitrary other industries. Yet, plants do benefit from other plants that belong to particular, vertically related upstream sectors. These cross-industry spillovers are quite sizeable, although they tend to be smaller than intra-industry spillover effects. Interestingly, a similar positive cross-industry effect cannot be found from plants in downstream industries. The number of plants in these sectors has no effect on a firm's TFP level, just as the number of plants in other industries that are neither important upstream suppliers nor downstream customers has no effect either.

We believe that our results reconcile the findings by Henderson (2003), Cingano and Schivardi (2004) and Mayer et al. (2008) on the dominance of localization effects, and the aforementioned empirical literature following Holmes (1999) that has emphasized vertical linkages and cross-industry effects by using a more aggregate empirical approach. Furthermore, we emphasize an asymmetry between upstream and downstream spillovers, which – to the best of our knowledge – has not been noted in the literature so far. The only other study that we are aware of, which also uses disaggregate data to address the relevance of vertical linkages as an agglomeration force, is the recent paper by Amiti and Cameron (2007). They use detailed wage data of Indonesian plants and also find evidence for input-output linkages. Plants pay significantly higher wages if located in regions with abundant upstream suppliers and in regions with large local demand. A high concentration of firms from the own industry, however, is found to reduce wages. In our paper we address the impact of similar variables on plant-level TFP rather than on wages. We find evidence for both spillovers across vertically related industries *and* positive intra-industry effects, the latter of which is consistent with the previous literature on localization effects.

The rest of this paper is organized as follows: In section 2 we describe the data set and provide a descriptive overview. Section 3 is devoted to the description of our empirical approach, and section 4 presents the results. Section 5 concludes.

2. Data and basic patterns

The empirical analysis uses establishment- or plant-level data from the manufacturing sector of Chile for the period 1990 throughout 1999. The data was obtained from the Annual National Industrial Survey (ENIA) carried out by the National Institute of Statistics of Chile. This survey covers all Chilean manufacturing plants with 10 or more workers. For each plant and year, the ENIA collects data on production, value added, sales, employment, wages, exports, investment, depreciation, energy usage, foreign technology licenses, and other plant characteristics. Each plant has a unique identification number, which allows us to follow plants over time. We have also information about the sector in which the plant operates (based on the International Standard Industrial Classification, ISIC rev 2), and the region in which the plant is located. Chile is divided into 13 regions as shown in a map in figure 1. Using 4-digit industry level price deflators, all monetary variables were converted to constant pesos of 1985. The capital stock at the plant level was constructed using the perpetual inventory method for each plant.[4]

[4] For the majority of plants, an initial value of the capital stock was available. This initial value was used to construct the capital stock data by adding investment and subtracting depreciation for each type of capital (machinery and equipment, buildings, and vehicles). For a small group of plants it was not possible to construct the stock of capital, so they were dropped from the data set.

Table 1 shows that an average of 4,911 plants operated during the period. Since Chile is a relatively natural-resource abundant country, it is not surprise that almost half of the plants produce natural-resource intensive products.[5] But sectors not based on natural resources are also important: 40% of plants produce apparel, textiles, metal products, printing, plastics, non-electrical machinery, and other chemical products. The large abundance of natural resources has determined, in part, that most plants are located in regions where natural resources are widely available. But there is a high concentration of plants in only a few regions. As seen in Table 2, the Region Metropolitana (RM), where the capital city (Santiago) is located, accounts for almost 60% of the total number of establishments operating in the manufacturing sector. Taken together, this region and three more regions (Biobío, Valparaíso, and Los Lagos) account for 82% of the plants. Interestingly, the regions located at the extreme north (Tarapacá, I) and extreme south (Magallanes, XII) account for only 3.7% of the total number of plants.

[TABLE 1 HERE]

[TABLE 2 HERE]

[FIGURE 1 HERE]

To measure productivity at the plant level we estimate a Cobb-Douglas production function for each 3-digit industry using the method proposed by Olley and Pakes (1996) and later modified by Levinsohn and Petrin (2003), which corrects the simultaneity bias associated with the fact that productivity is not observed by the econometrician but it may be observed by the firm. The residuals of these regressions are then used to measure productivity, or total factor productivity (TFP) at the plant level, which we will use below as the dependent variable in the empirical analysis (see appendix for details).

3. Empirical approach

The dependent variable in our analysis is plant level TFP (in logs), which is denoted by $\ln(p_{i,s,r,t})$ for firm *i*, sector *s*, region *r*, and time period *t*. Our main control variables

[5] Natural-resource intensive products include food, beverages, wood, paper, industrial chemicals, petroleum products, rubber, glass, non-metallic minerals, iron, steel, and non-ferrous metals.

capture intra-industry and cross-industry spillovers effects across plants, where we take into account vertical industry relations. Furthermore, we control for several important plant-specific characteristics as well as for several types of fixed effects. We now discuss the specification of all control variables in turn.

3.1. Intra-industry and cross-industry spillover effects

Localized intra-industry spillovers are measured by the number of firms from the same industry *s* and region *r* at time *t*. We denote this variable by $N_{s,r,t}$. Intra-industry spillovers are not necessarily localized, however. They may be internal to industry *s* but extend across regional borders. This is especially true in a small country like Chile. To allow for non-localized intra-industry spillovers we also include the number of plants from sector *s* that are located in regions other than *r* at time *t*. This variable is denoted by $N_{s,-r,t}$.

We do not use (inevitably imperfect) measures for the distance between the Chilean regions, but we adopt a somewhat simpler approach that makes use of the unique geographical structure of the country. Since Chile basically extends only in the North-South direction, almost every region has exactly one neighbor in the North and one in the South (see Figure 1 above).[6] When controlling for $N_{s,-r,t}$ we distinguish in some specifications between the number of plants (from sector *s*) that are located in neighboring and in non-neighboring regions of *r*, respectively. Thereby we analyze if intra-industry effects are localized in Chile, without having to measure distances explicitly.[7]

Cross-industry productivity spillovers are measured in a similar way. In the basic regression we include the number of firms from different industries located in the same region in year *t*, $N_{-s,r,t}$. This general measure does not take into account how closely related the different industries are. It is well conceivable, however, that cross-industry

[6] There are a few exceptions. The regions of Tarapacá and Magallanes at the top north and the top south, respectively, have only one neighbor. The region of Valparaíso (V) is bordered in the south by regions Metropolitana (RM) and the Libertador Bernardo O'Higgins (VI), which is in turn bordered by the V and the RM on the north. Thus, regions V and VI have three neighbor regions.

[7] Detailed micro-geographic information about plant locations, comparable to the type of data that is used by Rosenthal and Strange (2008) is – to the best of our knowledge – not available for the case of Chile.

spillovers are more important among industries that are closely related along the value chain. A plant from, say, primary metal manufacturing may be more productive if many plants from related industries, such as mineral mining or machinery, are located close by, whereas the presence of plants from, say, the apparel or wine industry has no notable effect.

Ideally, we would like to have access to detailed information about each plant's structure of purchased inputs from other plants. Such data is not available, however, and we have to construct proxies. To account for the proximity of the different sectors we make use of the aggregate Chilean input-output (I-O) matrix for the year 1996. This matrix entails the aggregate value (in pesos) of intermediate goods that every industry *s* purchases from, and sells to every industry ℓ. It turns out that most industry-pairs are actually linked as upstream suppliers and as downstream customers at the same time. That is, most industries *s* are both upstream and downstream to every other industry ℓ. However, we can use the input-output matrix to construct a "ranking" of industrial proximity. For every industry *s* we can find the *k=1,2,3,…* most important upstream, and the m=*1,2,3,…* most important downstream industries with which sector *s* is most closely linked in the aggregate. To give an example, the metal products sector (ISIC 381) purchases most of its inputs from the iron and steel industry (ISIC 371), followed by the non-ferrous metals sector (ISIC 372).[8] In Chile, the metal products sector sells most of its intermediate products to the food sector (ISIC 311 and 312), followed by the plastics products sector (ISIC 356).

Equipped with this aggregate ranking, we calculate (for every plant *i* in the data set) how many plants from the *k=1,2,3,…* most important upstream industries, and how many plants from the *m=1,2,3,…* most important downstream industries are located in the same region *r* in year *t*. These respective numbers of plants in region *r* are denoted by $U^k_{s,r,t}$ and D^m_{srt}, which are subsets of $N_{-s,r,t}$. Whereas $N_{-s,r,t}$ measures how many plants from different industries are located in region *r* in total, the variables $U^k_{s,r,t}$ and $D^m_{s,r,t}$ show how many plants are located in region *r* that can be classified as belonging to an important upstream or, respectively, downstream industries of sector *s*. The value of the

[8] Not surprisingly, the iron and steel industry purchases most of its inputs from the iron mining industry, while the non-ferrous sector's main supplier is the copper mining industry.

indices k and m define what precisely we mean by "important". For example, for a plant from the metal products sector (ISIC 381), $U^{1}_{ISIC381,r,t}$ counts the number of plants from the iron and steel industry in the same region and year, $D^{2}_{ISIC381,r,t}$ counts the number of plants from the food and from the plastic products sector, and so on. Using these definitions we then calculate the number of plants in the same region but not in the most important upstream sectors $N^{-U}_{-s,r,t} = N_{-s,r,t} - U^{k}_{s,r,t}$, and the number of plants in the same region but not in the most important downstream sectors: $N^{-D}_{-s,r,t} = N_{-s,r,t} - D^{k}_{s,r,t}$.

An underlying assumption of this procedure is that vertical relationships between industries are roughly stable, both across regions and over time, since we apply the same ranking of industrial proximity to plants from all regions and years. We are forced to do this, since regional I-O tables do not exist in Chile, and even the national I-O matrix is not published on an annual basis. Notice, however, that we do not assume that the precise input-output coefficients are the same across all regions and years, but only that the same ranking of closely related upstream and downstream sectors applies. We believe that this assumption is not very restrictive. The basic specifications that we estimate are given by

$$\begin{aligned}\ln\left(p_{i,s,r,t}\right) = \beta_0 + \beta_1 \cdot N_{s,r,t} + \beta_2 \cdot N_{s,-r,t} + \beta_3 \cdot N_{-s,r,t} + \Omega' \cdot Z_{i,s,r,t} + \\ \delta_{r,t} + \delta_{s,t} + \delta_{i,r} + \varepsilon_{i,s,r,t},\end{aligned} \tag{1}$$

$$\begin{aligned}\ln\left(p_{i,s,r,t}\right) = \beta_0 + \beta_1 \cdot N_{s,r,t} + \beta_2 \cdot N_{s,-r,t} + \beta_3 \cdot N^{-U}_{-s,r,t} + \beta^{k}_{U} \cdot U^{k}_{s,r,t} + \\ \Omega' \cdot Z_{i,s,r,t} + \delta_{r,t} + \delta_{s,t} + \delta_{i,r} + \varepsilon_{i,s,r,t},\end{aligned} \tag{2}$$

$$\begin{aligned}\ln\left(p_{i,s,r,t}\right) = \beta_0 + \beta_1 \cdot N_{s,r,t} + \beta_2 \cdot N_{s,-r,t} + \beta_3 \cdot N^{-D}_{-s,r,t} + \beta^{m}_{D} \cdot D^{m}_{s,r,t} + \\ \Omega' \cdot Z_{i,s,r,t} + \delta_{r,t} + \delta_{s,t} + \delta_{i,r} + \varepsilon_{i,s,r,t},\end{aligned} \tag{3}$$

where $Z_{i,s,r,t}$ and the $\delta' s$ are plant-specific characteristics and different fixed effects, which are discussed in greater detail below, and $\varepsilon_{i,s,r,t}$ is a standard error term. Since estimating a regression with plant level data but including sector time-varying variables may underestimate the standard errors (Moulton, 1990), we correct this problem by clustering the standard errors at the 3-digit sector-region-year level.

In the basic equation (1) we only account for the number of plants in different sectors in general, without taking into account how closely the industries are related. This is done in (2) and (3), where we control for the number of plants from the k most important upstream and the m most important downstream industries. Below we run several specifications where we successively increase the value of k and of m.

Notice that our measurement of intra- and cross-industry spillovers relies on the number of plants. Previous approaches have measured localization effects with an aggregate (output or employment) share of sector s in region r, and cross-industry or urbanization effects by some aggregate index of the local economic structure (e.g. a Herfindahl or diversity index).[9] Our specification renders a straightforward interpretation of the estimated coefficients: By how much does (log) TFP increase with one additional plant in the respective industry and region?

3.2. Plant-specific characteristics

We include several plant-specific controls $Z_{i,s,r,t}$ in the regressions. In particular we consider plant size (number of employees), plant age, and the square of both variables, in order to account for internal scale economies and life-cycle effects that are likely to affect firm productivity. The plant-specific wage premium for skilled workers relative to unskilled workers is included in order to capture the skill intensity of firms. Finally, we include dummies that indicate whether the plant is an exporter, whether it has foreign ownership, and whether it uses foreign technology licenses.

The inclusion of these dummy variables is motivated by the recent literature on firm heterogeneity in international trade (e.g., Bernard and Jensen 1999; Melitz 2003), which shows that exporting firms are more productive than non-exporters.[10] By simultaneously controlling for the plants' export status and for spillover effects from the local industrial environment we also build a bridge between these two active empirical literatures on firm productivity. We can, for example, analyze if the impact of spillover effects remains robust when controlling for export status, if exporter are affected differently from agglomeration forces than non-exporters, etc.

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[9] See e.g. Cingano and Schivardi (2004).

[10] See López (2005) for a survey on this literature.

[TABLE 3 HERE]

Table 3 provides an overview of our control variables. As can be seen from the table, there is huge variation in plant-level productivity as well as in plant size. About 20% of Chilean plants are exporters. Skilled workers receive on average more than twice the wage of unskilled workers, again with huge variation across plants.

3.3. Fixed effects and unobserved heterogeneity

In all regressions we include region-time ($\delta_{r,t}$) and industry-time fixed effects ($\delta_{s,t}$) in all regressions. These two sets of dummies filter out idiosyncratic (yet, possibly time varying) productivity differentials between particular Chilean regions or industries that are independent of spillovers or plant-specific characteristics. This is important for a small open economy like Chile where some regions like the capital and primate city Santiago, and some sectors like the wine industry play unique roles and are exposed to asymmetric shocks from the world market.

In addition we include plant-region fixed effects $\delta_{i,r}$. This is crucial for two reasons. Firstly, it acknowledges that productivity of certain plants may be affected by location-specific features or comparative advantages (like access to natural resources or infrastructure) which are important determinants of location decisions and which have to be distinguished from Marshallian externalities (Ellison and Glaeser, 1997).

Furthermore, the plant-region fixed effects address the issues of unobserved heterogeneity and spatial sorting, which have been central to the agglomeration literature in recent years. Spatial sorting is discussed intensively in agglomeration studies that rely on individual wage data (see e.g. Glaeser and Maré 2001, Gould 2007, Combes et al. 2008). As workers choose their location endogenously within a country, it is not clear if workers receive higher wages in dense areas because of agglomeration effects, or if the wage premium is the result of self-selection of more productive workers into dense areas. Including worker fixed effects to control for unobservable worker characteristics is a standard procedure of addressing ability bias in this type of studies, given that exogenous instruments which predict location but not current productivity are utterly difficult to find. The issue for this paper is quite similar: Since plant location is not random, OLS estimation may pick up self-selection of (unobservably) more productive plants into particular locations, rather than causal effects of location for individual firm productivity. It is essentially for this reason that Henderson (2003) also includes plant-region fixed effects in his study.[11] We follow this well established approach, which implies that all identification comes from the *change* of the firms' location over time.

4. Results

4.1. Basic results

Table 4 shows our basic results from the benchmark specification, equation (1). In column 1 we control for the number of firms from the same industry but different region, $N_{s,r,t}$, without distinguishing between neighboring and non-neighboring regions. In column 2 we make this distinction. Common to both specifications is that we only include the number of firms from the same region but different industries, $N_{-s,r,t}$, without taking into account the degree of vertical industry relations at this point.

[TABLE 4 HERE]

We find clear evidence for the existence of intra-industry productivity spillovers. The more plants operate in the own local industry, the larger is plant-level TFP on average. An additional plant in the same industry and region increases productivity of existing plants by 0.0011% on average. Yet, these intra-industry spillovers do not appear to be strongly localized in Chile. We find positive effects of the same magnitude from the number of plants in the own industry but in different regions. When distinguishing between neighboring and non-neighboring regions, we find no notable difference, which suggests that there is no strong distance decay in intra-industry spillover effects. This result is at odds with some previous findings from the literature, in particular with those by Rosenthal and Strange (2003) and Amiti and Cameron (2007), who find a rather sharp distance decay of spillover effects in the US and in Indonesia, respectively.

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[11] Mayer et al. (2008) also adopt a fixed effects estimation to address unobserved firm heterogeneity.

A plausible reason for this difference may be that Chile is a much smaller country, where most economic activity takes place in a geographically more limited area.[12] Also the primacy of Santiago, where most sophisticated plants are located, may explain parts of this result. A plant located in a remote region may benefit from intra-industry spillovers from Santiago, rather than from spillovers from other plants located nearby.

The second basic result that follows from table 4 is that we find no evidence for general cross-industry spillovers or urbanization effects. The number of plants from other industries in the same region has no significant impact on TFP. These results are consistent with the findings by Henderson (2003) and Cingano and Schivardi (2004), who also found only intra- but no robust evidence for inter-industry spillover or urbanization effects. We will qualify this finding below, when we distinguish between plants from sectors with which industry *s* has strong vertical relations.

Finally, we obtain plausible results for the plant-specific covariates. The coefficients for plant age and plant size have the expected sign, although they are not significant. Firms that pay higher wage premium to skilled labor are more productive, which strongly suggests that skill intensive firms have higher productivity. Yet, the most important finding for the plant-specific characteristics, in our view, is the clear evidence that exporting firms are more productive. Plants that export are, on average, 5% more productive than non-exporters.[13] This result, which is in line with the vast recent literature in international trade, does not conflict with the impact of intra-industry spillovers. As seen in columns (3) and (4) of Table 4, dropping the exporter dummy leaves the other coefficients virtually unchanged. No effect can be found, on the other hand, for foreign ownership or foreign technology licensing.

[12] Although the North-South-extension of Chile is huge (around 4,600 km, which is roughly the distance between San Francisco to New York, or from Edinburgh to Baghdad.), there is very little manufacturing activity in the very North and in the very South (taken together, the two northern regions and the two southern regions account for less than 7% of employment and just over 10% of value added).

[13] Since our specifications include plant-location fixed effects, the estimated productivity advantage of exporters is lower than what has been found in empirical studies of trade (see, for example, Alvarez and López, 2005).

4.2. Spillovers from upstream and downstream industries

In table 5 we report the results for the specifications (2) and (3). In the upper panel A we include number of firms (in the same region) from different industries in general, but we also control explicitly for the number of firms from the *k* most important upstream industries of sector *s*. The five columns in the panel refer to the estimations where we have set *k=1,2,3,4,5*, i.e., where we gradually enlarge the circle of “important upstream industries”. In panel B of table 5 we report the results of analogous regressions, where we distinguish the *m=1,2,3,4,5* most important downstream industries of sector *s*. [14]

[TABLE 5 HERE]

Turning to the upper panel A at first, we find that the number of firms in important upstream industries has a positive impact on productivity of plants in sector *s* as long as $k \leq 3$. That is, we find evidence for cross-industry productivity spillovers from plants that belong to the three most important upstream sectors. By increasing the value of *k*, i.e., by applying a laxer definition of an important upstream sector, we obtain decreasing coefficients for the productivity spillover. This suggests that an additional plant in the single most important upstream sector of industry *s* raises plant-level productivity in *s* stronger than an additional plant in the second- or third-most important supplier industry. Beyond a certain level, when $k \geq 4$, we find no significantly positive cross-industry spillovers anymore.

The finding of positive intra-industry spillovers remains robust. In fact, an additional plant in the own industry (and region) raises firm-level TFP stronger than an additional plant in the most important upstream industry (0.00154 vs. 0.00087). The effect is roughly twice as large. This means that an additional plant in a given region and industry increases productivity of plants in the same region and industry by 0.00154%, and increases productivity of plants in downstream sectors located in the same region by 0.00087%. Also the result remains robust that plants from different industries, which do not belong to the *k* most important upstream suppliers, have no effect on plant-level productivity in sector *s*. The estimated coefficients for the plant-specific covariates are omitted for brevity, but they are virtually unchanged compared to table 4.

[14] As a robustness check we have also estimated specifications where the number of plants in the first, second, third, … most important upstream (downstream) sector has been included separately and one at a time. Qualitative results have been similar to those reported in the paper.

Turning to the lower panel B of table 5, we have performed a similar exercise for the *m* most important downstream industries. Interestingly, we find no evidence at all for productivity spillovers from plants in downstream sectors to plants in sector *s*. This is true even for plants from the single most important downstream industry (*m=1*). In all specifications we obtain coefficients that are not statistically distinguishable from zero.[15] The finding of positive intra-industry spillovers remains again robust.

All in all, table 5 suggests that cross-industry productivity spillovers do not exist in general, but they do exist for firms that belong to the most important upstream suppliers. Intra-industry spillovers also exist, and they tend to be even stronger than the spillovers from upstream industries. There is no evidence for productivity spillovers from downstream industries, not even from the very closely related ones. [16]

4.3. Plant size and spillovers

Different plants may be affected differently from agglomeration effects. In particular, small plants may rely stronger on the externalities created by the industrial environment than large plants do. This idea is developed, for example, in Henderson (2003) and in Rosenthal and Strange (2003). Henderson finds indeed that localization effects lead to stronger productivity gains in small plants.

We have checked whether a similar result holds for the cross-industry productivity spillovers from vertically related industries that are at the centre of interest in this paper. We re-estimated regressions (2) and (3), and included a term that interacts the number of plants in upstream (downstream) industries, $U^k_{s,r,t}$ (respectively, $D^m_{s,r,t}$), with individual plant size measured by the number of employees. Table 6 shows the results.

[TABLE 6 HERE]

[15] The coefficient for the number of plants in different industries (except for the *m* most important downstream sectors) is now positive and significant in some specifications (for *m=1* and *m=2*). This is due to the fact that the most important upstream sectors are included in this figure whereas the number of plants in the most important downstream sectors is separately controlled for.

[16] We now also find some evidence for localization of these intra-industry effects, since the effect of an additional plant in the same industry is somewhat stronger when the increase occurs in the same region (0.00154 vs. 0.00118). Cross-regional spillovers in the same industry remain important, however.

The results strongly suggest that small plants benefit more from spillovers by upstream firms than large firms. The coefficient on the number of upstream plants $U_{s,r,t}^{k}$ is significantly positive (and decreasing in size when we increase *k*), but the interaction term is negative and highly significant. Spillovers from other industries that are not important upstream suppliers still play no significant role, even if we include interaction terms. Productivity spillovers from firms in downstream industries continue to be insignificant.

These results can be seen as a robustness check of our main conclusion that there is evidence for intra-industry and for cross-industry productivity spillovers from important upstream sectors. These cross-industry spillover effects are more important for small than for large plants. This result is consistent with Henderson's results, who found that intra-industry localization effects are also stronger for small firms.

5. Conclusions and discussion

In this paper we have analyzed the impact of intra- and cross-industry productivity spillovers for Chilean plants (1990-1999). We find robust evidence for positive intra-industry effects, although the effects are not so strongly localized in Chile. We also find evidence for cross-industry spillovers from important upstream sectors. There is no evidence, however, for productivity spillovers from downstream sectors or from other, unrelated industries.

Our results are informative for the industrial scope of spillovers. According to our findings, firms benefit from other firms that operate in the same industry and experience individual productivity gains. This finding is consistent with so-called Marshall-Arrow-Romer (MAR) externalities, and implies that industrial clustering and regional specialization are likely to offer productivity gains to the firms inside the cluster.

Yet, regional planners in practice do usually not think of clusters simply as the spatial concentration of firms from a single industry, but as a spatial concentration of firms from several closely related industries. This policy approach is built on the assumption that cross-industry spillovers exist, but the empirical literature on agglomeration and firm productivity has not found much supportive evidence for such effects so far.

In this paper we account for the vertical relationships between different industries. Thereby we distinguish, for the first time, productivity spillovers between closely related industries and spillovers between sectors that are not closely related. We find that no ubiquitous cross-industry productivity spillovers exist. Firms do not benefit from other firms in arbitrary industries. We do find, however, that firms benefit from other firms that are active in closely related (upstream) industries.

Previous studies that addressed the impact of spillovers on plant-level productivity (Henderson 2003, Cingano and Schivardi 2004, Mayer et al. 2008) have strongly emphasized the importance of intra-industry effects (MAR externalities) only. Our results are not opposite to theirs, since we also find that intra-industry effects are the most important type of spillover. Yet, we also find evidence for the idea of "cross-fertilization", sometimes attributed to the name of Jacobs-externalities. This cross-fertilization does not arise between arbitrary industries, however.

Firms benefit from adjacent upstream suppliers, and are more productive the more plants from important upstream industries are co-located in the same region. The producer of the intermediate goods is not significantly more productive, however, if the downstream customers are located close by. How should one interpret this result on the asymmetry between upstream and downstream industries? One possible interpretation relies on the concept of knowledge spillovers that may be behind the productivity effects that we have measured in this paper. According to our results, there are Jacobs-type inter-industry knowledge spillovers which flow into the same direction as the intermediate goods flow along the vertical value chain: From upstream to downstream industries, but not the other way around. Such knowledge flows may consist of information about specific characteristics of the intermediate goods, how to handle and use the purchased inputs, etc. Knowledge flows from downstream to upstream firms, e.g. about the specific needs of the local customers, do not seem to be so pervasive – at least in Chile.

Appendix: The Levinsohn and Petrin Technique

Consider the following Cobb-Douglas production function:

$$y_{it} = \beta_k k_{it} + \beta_s l_{it}^s + \beta_u l_{it}^u + \omega_{it} + \varepsilon_{it}, \qquad \text{(A1)}$$

where y_{it} is the log of value added, k_{it} is the log of capital, l_{it}^s is the log of skilled labor, and l_{it}^u is the log of unskilled labor. The terms ω_{it} and ε_{it} are unobserved by the econometrician but ω_{it} is observed by the firm. This introduces a simultaneity problem, since ω_{it} is likely to be correlated with the choice of capital and labor. Levinsohn and Petrin (2003) assume that $m_{it} = m_{it}(k_{it}, \omega_{it})$, where m_{it} is the intermediate input, and show that this relationship is monotonically increasing in ω_{it}. Thus, the intermediate input function can be inverted to obtain $\omega_{it} = \omega_{it}(k_{it}, m_{it})$. Then, equation (A1) becomes:

$$y_{it} = \beta_s l_{it}^s + \beta_u l_{it}^u + \phi(k_{it}, m_{it}) + \varepsilon_{it}, \qquad \text{(A2)}$$

where $\phi(k_{it}, m_{it}) = \beta_k k_{it} + \omega_{it}(k_{it}, m_{it})$. Levinsohn and Petrin estimation involves two steps. In the first step, equation (A2) is estimated treating $\phi(k_{it}, m_{it})$ non-parametrically, which gives the estimates for the labor inputs. The second step identifies β_k. Assuming that ω_{it} follows a first-order Markov process: $\omega_{it} = E[\omega_{it} / \omega_{it-1}] + \xi_{it}$, and given that k_{it} is decided at *t-1*, then $E[\xi_{it} / k_{it}] = 0$, which implies that ξ_{it} and k_{it} are uncorrelated. This moment condition is then used to estimate the elasticity of capital β_k. As in Levinsohn and Petrin (2003), we use consumption of electricity as the intermediate input that allows the identification of the elasticity of capital. Finally TFP is calculated as: $TFP_{it} = \exp\left(y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_s l_{it}^s - \hat{\beta}_u l_{it}^u\right)$.

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Table 1: Number of Plants by 3-Digit ISIC Sector and Year

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average
Food	1,339	1,349	1,389	1,376	1,356	1,338	1,450	1,350	1,350	1,247	1,354
Food - Miscellaneous	71	80	79	78	84	85	93	83	84	78	82
Beverages	95	93	94	87	86	84	86	86	88	83	88
Textiles	364	377	386	357	360	356	369	333	307	277	349
Apparel	312	335	349	337	329	313	366	293	260	255	315
Leather Products	51	54	62	58	54	48	48	39	35	32	48
Footwear	154	157	159	146	168	161	167	144	130	108	149
Wood Products	328	320	327	390	385	380	398	367	346	312	355
Furniture	117	123	129	150	155	153	184	159	155	137	146
Paper	66	71	73	69	77	83	86	81	78	73	76
Printing	188	200	209	224	217	212	226	208	199	195	208
Industrial Chemicals	73	74	79	74	71	67	65	64	67	58	69
Other Chemicals	171	184	192	195	198	198	208	185	183	172	189
Petroleum Refineries	2	2	2	2	2	3	3	2	5	4	3
Petroleum Products	17	20	23	20	21	19	20	20	18	16	19
Rubber Products	52	57	59	67	67	64	65	56	63	56	61
Plastics	198	212	221	261	268	283	271	254	234	225	243
Ceramics	20	22	21	21	19	24	20	14	11	7	18
Glass	18	17	16	19	18	19	22	21	21	22	19
Non-Metallic Minerals	117	134	147	148	170	164	175	159	158	152	152
Iron and Steel	31	32	31	28	35	27	25	27	24	27	29
Non-Ferrous Metals	37	35	34	41	32	45	49	46	48	33	40
Metal Products	351	374	405	420	444	475	532	493	482	429	441
Non-Electrical Machinery	178	188	192	209	199	225	236	213	217	184	204
Electrical Machinery	50	59	60	63	63	63	72	58	59	51	60
Transport Equipment	107	116	118	122	122	133	125	115	108	92	116
Professional Equipment	18	19	20	18	19	20	23	22	20	19	20
Other Manufacturing	49	54	55	56	59	65	63	68	65	56	59
Total Manufacturing	4,574	4,758	4,931	5,036	5,078	5,107	5,447	4,960	4,815	4,400	4,911

Table 2: Number of Plants by Region and Year

Region	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	Average
Tarapacá	132	128	122	118	132	128	131	134	139	117	128
Antofagasta	108	107	114	107	98	119	136	128	132	103	115
Atacama	48	52	60	52	52	55	57	49	53	32	51
Coquimbo	91	96	107	107	105	93	99	99	99	87	98
Valparaíso	360	359	398	390	391	400	423	365	367	353	381
Libertador Bernardo O'Higgins	130	126	135	135	124	128	141	137	120	96	127
Maule	174	176	184	194	194	195	196	189	177	168	185
Biobío	479	476	474	531	535	518	539	535	549	521	516
Araucanía	99	94	100	104	109	104	114	101	117	117	106
Los Lagos	182	185	199	209	203	215	234	211	223	195	206
Aisén	18	20	20	20	21	20	20	18	18	17	19
Magallanes	64	57	60	54	55	56	52	50	48	39	54
Metropolitana – Santiago	2,689	2,882	2,958	3,015	3,059	3,076	3,305	2,944	2,773	2,555	2,926
Total Country	4,574	4,758	4,931	5,036	5,078	5,107	5,447	4,960	4,815	4,400	4,911

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln(Total factor Productivity)	40,454	6.9	1.1	-4.6	12.7
ln(Employment)	40,454	3.8	1.0	1.1	8.3
Export Dummy	40,454	0.2	0.4	0	1
Foreign Ownership Dummy	40,454	0.1	0.2	0	1
ln(Age)	40,454	2.1	0.8	0	3.0
Foreign Licenses Dummy	40,454	0.1	0.2	0	1
Wage Premium	40,454	2.7	3.0	0	169.7
Number of Plants Same Industry and Region	40,454	166.7	155.0	1	577
Number of Plants Same Industry Different Region	40,454	359.1	451.4	1	1,440
Number of Plants Same Region Different Industry	40,454	1,743	1,232	7	3,304
Number of Plants in the Most Important Upstream Sector (same region)	40,454	81.0	120.8	0	635
Number of Plants in the Two Most Important Upstream Sectors (same region)	40,454	184.8	189.0	0	800
Number of Plants in the Three Most Important Upstream Sectors (same region)	40,454	262.8	241.6	0	896
Number of Plants in the Four Most Important Upstream Sectors (same region)	40,454	325.5	299.2	0	1,218
Number of Plants in the Five Most Important Upstream Sectors (same region)	40,454	354.3	327.3	0	1,218
Number of Plants in the Most Important Downstream Sector (same region)	40,454	192.2	224.9	0	635
Number of Plants in the Two Most Important Downstream Sectors (same region)	40,454	298.6	310.0	0	1,038
Number of Plants in the Three Most Important Downstream Sectors (same region)	40,454	371.5	339.0	0	1,183
Number of Plants in the Four Most Important Downstream Sectors (same region)	40,454	457.7	375.1	0	1,301
Number of Plants in the Five Most Important Downstream Sectors (same region)	40,454	492.7	381.8	0	1,301

Table 4: Basic Results

	(1)	(2)	(3)	(4)
Number of Plants Same Industry and Region	0.00108	0.00110	0.00108	0.00109
	(2.43)*	(2.45)*	(2.46)*	(2.48)*
Number of Plants Same Industry Different Regions	0.00117		0.00118	
	(3.65)**		(3.69)**	
Number of Plants Same Industry Neighbor Regions		0.00106		0.00105
		(2.60)**		(2.59)**
Number of Plants Same Industry Non-Neighbor Regions		0.00120		0.00121
		(3.59)**		(3.64)**
Number of Plants Same Region Different Industry	0.00015	0.00015	0.00014	0.00014
	(0.46)	(0.46)	(0.41)	(0.41)
Plant Employment	0.03282	0.03273	0.03481	0.03470
	(0.60)	(0.60)	(0.64)	(0.63)
Plant Employment Squared	-0.01221	-0.01219	-0.01203	-0.01201
	(1.79)+	(1.79)+	(1.77)+	(1.77)+
Plant Export Dummy	0.05264	0.05257		
	(4.30)**	(4.29)**		
Plant Foreign Ownership Dummy	0.02725	0.02723	0.02987	0.02984
	(0.89)	(0.89)	(0.98)	(0.98)
Plant Age	0.03118	0.03126	0.03209	0.03218
	(1.40)	(1.40)	(1.44)	(1.44)
Plant Age Squared	-0.00058	-0.00066	-0.00064	-0.00073
	(0.03)	(0.04)	(0.04)	(0.04)
Plant Foreign Licenses Dummy	0.02022	0.02031	0.02124	0.02133
	(1.23)	(1.24)	(1.29)	(1.30)
Plant Wage Skilled / Wage Unskilled Labor	0.01713	0.01713	0.01717	0.01717
	(8.75)**	(8.75)**	(8.75)**	(8.75)**
Observations	40,454	40,454	40,454	40,454
R-squared	0.8501	0.8501	0.8500	0.8500

Robust t-statistics in parentheses. **, *, +: significant at 1%, 5%, and 10%. Standard errors were clustered at the industry-region-year level. All regressions include industry-year and region-year dummy variables. The dependent variable is the natural log of TFP for each plant. Employment, and Age are in logs.

Table 5: Externalities from Upstream and Downstream Sectors

Panel A: From Upstream Sectors					
	(1)	(2)	(3)	(4)	(5)
Number Plants Same Industry and Region	0.00154	0.00154	0.00152	0.00117	0.00113
	(3.14)**	(3.14)**	(3.13)**	(2.60)**	(2.52)**
Number Plants Same Industry Different Regions	0.00118	0.00116	0.00113	0.00113	0.00116
	(3.67)**	(3.61)**	(4.57)**	(3.50)**	(3.61)**
Number Plants in Upstream Sectors Same Region	0.00087	0.00083	0.00083	0.00040	0.00027
	(2.14)*	(2.08)*	(2.30)*	(1.11)	(0.79)
Number Plants in Other Sectors Same Region	0.00057	0.00060	0.00061	0.00011	0.00012
	(1.61)	(1.70)+	(1.89)+	(0.31)	(0.34)
Number of Observations	40,454	40,454	40,454	40,454	40,454
R-Squared	0.8501	0.8501	0.8501	0.8501	0.8501

Panel B: From Downstream Sectors					
	(1)	(2)	(3)	(4)	(5)
Number Plants Same Industry and Region	0.00166	0.00165	0.00109	0.00109	0.00113
	(3.35)**	(3.34)**	(2.46)*	(2.44)*	(2.51)**
Number Plants Same Industry Different Regions	0.00105	0.00102	0.00112	0.00119	0.00120
	(3.19)**	(3.07)**	(3.37)**	(3.64)**	(3.70)**
Number Plants in Downstream Sectors Same Region	0.00046	0.00042	0.00004	0.00020	0.00028
	(1.23)	(1.14)	(0.10)	(0.55)	(0.76)
Number Plants in Other Sectors Same Region	0.00071	0.00067	0.00018	0.00014	0.00012
	(2.00)*	(1.90)+	(0.52)	(0.42)	(0.36)
Number of Observations	40,454	40,454	40,454	40,454	40,454
R-Squared	0.8501	0.8501	0.8501	0.8501	0.8501

Robust t-statistics in parentheses. **, *, +: significant at 1%, 5%, and 10%. Standard errors were clustered at the industry-region-year level. All regressions include plant controls, industry-year and region-year dummy variables. The dependent variable is the natural log of TFP of each plant. (1): 1 sector upstream/ downstream; (2): 2 sectors upstream/downstream; (3): 3 sectors; (4): 4 sectors; (5): 5 sectors.

Table 6: Externalities from Upstream and Downstream Sectors with Interaction Terms

Panel A: From Upstream Sectors

	(1)	(2)	(3)	(4)	(5)
Number Plants Same Industry and Region	0.00109	0.00107	0.00104	0.00116	0.00112
	(2.41)*	(2.38)*	(2.34)*	(2.57)*	(2.47)*
Number Plants Same Industry Different Regions	0.00118	0.00115	0.00114	0.00111	0.00115
	(3.67)**	(3.60)**	(3.55)**	(3.47)**	(3.59)**
Number Plants in Upstream Sectors Same Region	0.00108	0.00097	0.00097	0.00086	0.00074
	(2.23)*	(2.17)*	(2.30)*	(2.18)*	(1.91)+
Number Plants Upstream Sectors Same Region * Employment	-0.0002	-0.0002	-0.0002	-0.0001	-0.0001
	(2.78)**	(3.08)**	(3.49)**	(3.20)**	(3.63)**
Number Plants in Other Sectors Same Region	0.00021	0.00019	0.00017	0.00015	0.00014
	(0.61)	(0.56)	(0.49)	(0.44)	(0.42)
Number Plants in Other Sectors Same Region * Employment	-3E-05	-3E-05	-2E-05	-2E-05	-2E-05
	(3.29)**	(2.11)*	(1.23)	(1.42)	(1.22)
Number of Observations	40,454	40,454	40,454	40,454	40,454
R-Squared	0.8503	0.8503	0.8503	0.8503	0.8503

Panel B: From Downstream Sectors

	(1)	(2)	(3)	(4)	(5)
Number Plants Same Industry and Region	0.00162	0.00161	0.00108	0.00107	0.00155
	(3.27)**	(3.25)**	(2.42)*	(2.39)*	(3.10)**
Number Plants Same Industry Different Regions	0.00103	0.001	0.00109	0.00117	0.00117
	(3.13)**	(3.03)**	(3.33)**	(3.59)**	(3.62)**
Number Plants in Downstream Sectors Same Region	0.00029	0.00047	0.00022	0.00027	0.00054
	(0.71)	(1.21)	(0.56)	(0.71)	(1.30)
Number Plants Downstream Sectors Same Region * Employment	0.00003	-3E-05	-6E-05	-3E-05	0.00004
	(0.77)	(0.84)	(1.51)	(0.84)	(1.05)
Number Plants in Other Sectors Same Region	0.00085	0.00077	0.00029	0.00028	0.00083
	(2.39)*	(2.19)*	(0.84)	(0.82)	(2.31)*
Number Plants in Other Sectors Same Region * Employment	-5E-05	-4E-05	-4E-05	-4E-05	-7E-05
	(4.77)**	(3.70)**	(2.60)**	(2.74)**	(3.93)**
Number of Observations	40,454	40,454	40,454	40,454	40,454
R-Squared	0.8503	0.8503	0.8503	0.8503	0.8503

Robust t-statistics in parentheses. **, *, +: significant at 1%, 5%, and 10%. Standard errors were clustered at the industry-region-year level. All regressions include plant controls, industry-year and region-year dummy variables. The dependent variable is the natural log of TFP of each plant. (1): 1 sector upstream/ downstream; (2): 2 sectors upstream/downstream; (3): 3 sectors; (4): 4 sectors; (5): 5 sectors.

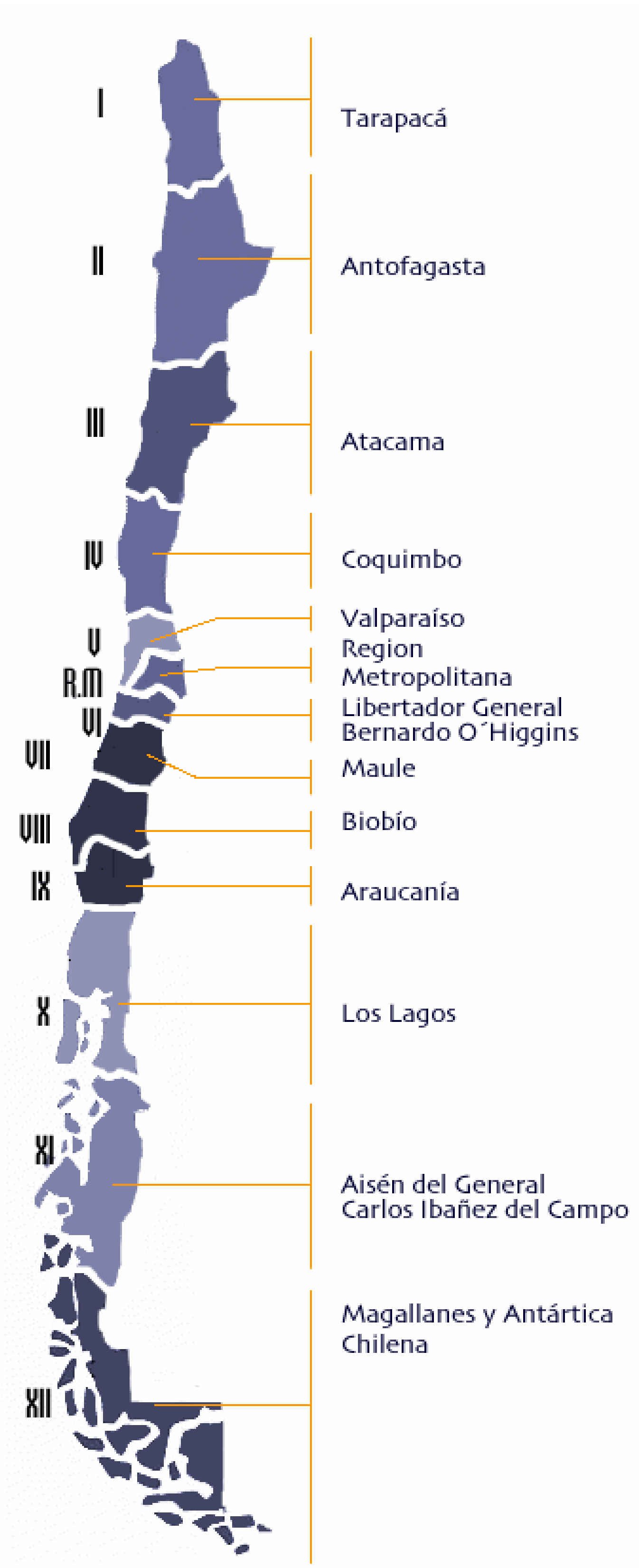

Figure 1: Regions of Chile