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The Advantages of Sectoral Diversity

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Abstract

This paper investigates whether the agglomeration of economic activity in regional clusters affects long-run manufacturing total factor productivity growth in an emerging market context. It explores a large firm-level panel dataset for Chile during a period characterized by high growth rates and rising regional income inequality (1992–2004). The findings are clear-cut. Locations with greater concentration of a particular sector did *not* experience faster growth in total factor productivity during this period. Rather, local sector diversity was associated with higher long-run growth in total factor productivity. However, there is no evidence that the diversity effect was driven by the local interaction with a set of suppliers and/or clients. The authors interpret this as evidence that agglomeration economies are driven by other factors, such as the sharing of access to specialized inputs not provided solely by a single sector, such as skills or financing.

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Explaining Local Manufacturing Growth in Chile: The Advantages of Sectoral Diversity

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1. Introduction

Episodes of fast growth accompanied by large increases in within-country income inequality were experienced across developing countries during the 1980s and 1990s. Chile was no exception: its economy experienced a sharp recovery after the 1980s' debt crisis and sustained growth throughout most of the 1990s and 2000s but growth was uneven across regions.[1] Between 1998 and 2000, Antofogasta, one of the richest regions, experienced growth in GDP per capita three times faster than that of La Araucaina, the poorest region (Duncan and Fuentes, 2006). This uneven growth was accompanied by the agglomeration of economic activity in a few industrial clusters. These clusters are groups of firms and related actors and institutions located near one another that draw productive advantage from their mutual proximity and connections (Cortright, 2006). The importance of firm agglomeration in industrial clusters for long-run growth has been emphasized by Porter (1990).

This paper investigates which type of agglomeration externalities was most conducive of the regional long-run growth pattern in Chilean manufacturing productivity between 1992 and 2004. We ask whether more specialized locations experienced faster long-run productivity growth relative to locations where economic activity was more diversified. We use a rich panel of firm-level data to obtain consistent estimates of total factor productivity (TFP) at the sector-location level. Our findings are supportive of the idea that locations with a more diverse set of activities exhibit higher long-run manufacturing TFP growth. We conjecture that geographical proximity led firms to share the access to specialized inputs provided by multiple sectors ranging from the availability

[1] See Bergoeing et al. (2002) and Gallego and Loayza (2002).

of relevant skills, accessible technology, adequate financing, infrastructure, advanced communications, and/or a sound regulatory climate.

The importance of scale economies for the agglomeration of economic activity has been emphasized since Marshall (1920). It is beneficial to locate where other firms in the same sector already produce due to the availability of intermediate goods, of a specialized labor force and large product demand, and to local knowledge diffusion. Jaffe et al. (1993), Branstetter (2001), and Keller (2002) show that knowledge externalities and technological spillovers are regional in scope. Consequently, knowledge accumulation in a geographical area can be a key driver of local productivity growth.

There are several theories on the types of externalities involved in this process. Marshall (1890), Arrow (1962), and Romer (1986) argue that the main agglomeration externality derives from a build-up of knowledge associated with communications among local firms in the same sector (*MAR externalities* or *localization economies*). The concentration of a sector in a location helps knowledge spillovers between firms and thus that sector's growth in the location. Alternative theories such as Jacobs (1969) focus on the importance of the cross-fertilization of ideas across different sectors to promote innovation and growth (*Jacobs externalities* or *urbanization economies*).[2] According to this theory, greater diversity of sectors in a location leads to higher sector growth. Finally, the degree of local competition in a sector can also influence knowledge creation and productivity growth. Under MAR externalities, a local monopoly benefits local growth by restricting the flow of ideas to others and allowing externalities to be

[2] *Urbanization economies* can consist of access to complementary services such as banking, a labor pool with multiple specializations, less costly infrastructure, and inter-industry information transfers.

internalized by the monopolist innovator.[3] In contrast, Jacobs (1969) and Nickell (1996) argue that competition is more conducive to innovation and productivity growth.[4]

Our paper relates to the empirical literature determining the type of externalities that would be more beneficial using employment growth to proxy for productivity growth. The use of employment growth is based on the assumption that more productive regions attract more workers in the long-run. However, this approach requires the assumption that employment and productivity growth correlate positively across regions. However, in several cases this might not be verified. First, if labor markets are local and labor supply shifts differently across regions (e.g., due to migration), employment and productivity growth do not necessarily covary. Second, if congestion externalities such as air pollution shift labor supply and demand simultaneously, the increase in employment growth may be smaller than the increase in labor demand. Third, if output demand is very inelastic in some sectors, increases in productivity may translate into small labor demand increases as firms are able to produce more output with the same labor input, and the sector's employment in the region may actually decline. Finally, if technological growth is labor-biased in some sectors, productivity growth may not translate into employment growth.[5] The evidence using employment growth is mixed. Glaeser et al. (1992) find that sectoral diversity in U.S. cities fosters employment growth in most industries while Henderson et al. (1995) find evidence of MAR externalities for mature capital goods and high-tech industries, but of Jacobs externalities only for the latter. Almeida (2007) and

[3] See Schumpeter (1942) on monopoly rents and innovation.

[4] *Porter externalities* designate externalities associated with a more competitive environment. Since Porter (1998) believes that intra-sectoral knowledge spillovers are the most relevant, the test for *Porter externalities* would embody both specialization and competition effects.

[5] See Almeida (2007) and Cingano and Schivardi (2002).

Combes (2000) show a negative effect of local concentration on sectoral employment growth in Portugal and France.

As richer sector and firm-level datasets became available, direct measures of productivity growth have been used in more recent studies. De Lucio et al. (2002) explore sector-level labor productivity growth for Spanish provinces while Almeida (2007) explores wage-adjusted growth for Portuguese regions: both find evidence of MAR externalities and no evidence of Jacobs or Porter externalities. Brülhart and Mathys (2008) find a weak negative effect of own-sector density but a positive effect of other-sector density on regional manufacturing labor productivity growth in 20 European countries. Dekle (2002) finds no evidence of MAR or Jacob externalities using sectoral manufacturing TFP growth measures for Japanese prefectures.

Notwithstanding the importance of the topic, much less evidence is available for developing or emerging economies. Hanson (1998) shows that within-industry agglomeration and local diversity have negative effects on employment growth of Mexican industries prior to trade liberalization. Henderson et al. (2001) provide evidence of MAR externalities and Jacobs externalities for industry-level labor productivity across South Korean cities, the latter being particularly relevant for high-tech industries. In contrast, Gao (2004) finds no effects of local specialization nor local diversity on output growth of 2-digit industries in Chinese provinces.

Henderson (2003) and Cingano and Schivardi (2004) are among the few studies exploring TFP measures computed at the micro level. Henderson (2003) shows that U.S. plants with higher TFP tend to locate close to other plants in their industry in the high-tech industry but not in the machinery industry. He finds little evidence of urbanization economies and weak benefits for TFP from the diversity of local economic activity. Henderson's specification relates plant-level time-varying output controlling for inputs (i.e., TFP levels) to time-varying agglomeration indices at the industry-location level hence is at a more disaggregated level than those in earlier papers. Cingano and Schivardi (2004) estimate production functions for Italian industries using firm-level survey data and following the Olley and Pakes (1996) methodology. Based on growth in industry-region averages of their firm-level TFP estimates, they find evidence of MAR externalities but no effects of sector competition or diversity.[6]

Our paper's contribution is threefold. First, we examine the importance of the local economic structure - concentration, specialization, and competition - for long-run TFP growth at the sector-location level using manufacturing census data for an emerging economy. We differ from Henderson (2003) and Lopez and Südekum (2009) since we focus on *long-run*, rather than on yearly effects of the local economic structure. Furthermore, we focus on TFP *growth*, rather than TFP *levels*, as our outcome variable. By considering long-run effects, our paper mitigates the potential concern of a spurious relationship between agglomeration and TFP growth that could arise from the correlation between unobserved determinants of TFP growth across sectors and regions and the agglomeration measures (Martin et al., 2009). Our inclusion of sectoral and regional fixed effects in some specifications explicitly addresses this concern. Second, our estimates of TFP are unbiased, obtained as the residuals from flexible translog production

[6] Lopez and Südekum (2009) examine a related question using Chilean plant-level data following Henderson (2003)'s approach. Their study differs from ours in several important respects. First, their empirical specification relates plant-level time-varying TFP levels to time-varying indices of concentration and diversity at the regional and sector level. Second, their indices of concentration and diversity are based on a simple count of the numbers of plants in particular sectors in the region. Third, their study covers an earlier sample period.

functions estimated following the Levinsohn and Petrin (2003) methodology (henceforth LP) which corrects for the potential simultaneity between input choices and productivity. Third, we try to shed light on the types of agglomeration forces at work by examining the importance of horizontal and vertical knowledge externalities. Horizontal knowledge externalities are defined as those whereby firms benefit from the knowledge of their local competitors (firms belonging to the same sector or producing very similar products) and vertical knowledge externalities are defined as those taking place through the proximity of local suppliers or clients.[7]

Our findings suggest that Chilean locations (*comunas*) with greater concentration of a certain sector have not grown faster over the 1992-2004 period. Our findings are more supportive of the view that local diversity in the sectoral composition is associated with faster long-run productivity growth. Our findings for Chile are consistent with Jacobs dynamic externalities under the assumption that the local knowledge stock grows over time and affects long-run growth as in Romer (1986). For example, the wood products sector in the Bibio province has a very high concentration index and its TFP in that location declined by 1.3% between 1992 and 2004. This contrasts with the food products sector whose TFP growth was more than 50% over the sample period in the province of Malleco which exhibits one of the highest sectoral diversities in the country. Our findings are in line with those for European regions by Brülhart and Mathys (2008). Our main findings are robust to multiple sensitivity checks such as including sector-

[7] One shortcoming of Cingano and Schivardi (2004) as well as our study is that both implicitly assume that the impact of the local economic structure on TFP growth works mainly through knowledge spillovers. The concept of knowledge spillovers is difficult to measure but some of its sources include managerial and accounting practices, production methods, or any other tacit and codified knowledge by which a firm transform inputs into output. However, the reduced form used in our empirical analysis is also compatible with alternative explanations of TFP growth. See Ciccone and Hall (1996) for two models that give rise to the same reduced form.

location characteristics such as the market size, possibly related to long-run TFP growth and the local economic structure. Our evidence does not support the idea that the estimated dynamic knowledge externalities are driven by either suppliers or clients. Rather, it suggests that those externalities are likely to occur through other types of interactions driven by the local proximity of sectors.

Our findings have important policy implications for the design of urban development policies. By showing that locations with a more diverse set of industrial activities exhibit faster TFP growth, our evidence does not support the formation of homogeneous but rather of heterogeneous industrial clusters. The rest of the paper is organized as follows. In Section 2, we discuss the data and the TFP measures. Section 3 describes the empirical methodology and the indices measuring the local economic structure. Section 4 presents the main findings and Section 5 discusses the sensitivity analysis. Section 6 concludes.

2. Data and TFP Measures

2.1. Data

We explore the Encuesta Nacional Industrial Annual (ENIA) - an annual census covering all formal Chilean manufacturing plants with more than 10 employees - between 1992 and 2004.[8] It is an unbalanced panel that includes an average of about 4,900 plants per year and provides comprehensive accounting information covering sales, intermediate

[8] Alvarez and Claro (2011) state that ENIA is a representative survey of Chilean manufacturing plants with 10 or more workers (their study focuses on the period 1996–2005) and the National Statistical Institute updates the survey annually by incorporating plants that started operating and by excluding plants that stopped operating in each year. There is some concern though that for more recent years the ENIA data has become less representative due to the attrition bias.

materials, energy, employment, investment, and detailed location and sector affiliation.[9] Plants are classified into 3-digit International Standard Industrial Classification (ISIC) sectors. Our estimating sample covers Chilean plants located in across 13 regions, 45 provinces, and 187 *comunas*. The unit of analysis in our empirical specifications is a 3-digit sector-*comuna* cell. Our estimating sample includes 853 sector-*comunas* which include on average 5 firms as shown in Table 1.[10]

2.2 TFP Measures

Our empirical approach relates long-run TFP growth of a sector-location to the local economic structure in 1992. We proceed in two steps to obtain estimates of TFP growth at the sector-location level. First, we obtain firm-level TFP estimates based on the Chilean dataset. Second, we average these firm-level TFP estimates up to the sector-location level and correspondingly compute TFP growth.

To implement the first step, we assume that within each 2-digit ISIC sector, firm *i* produces output based on a general and flexible translog production function in period *t*:[11]

$$\ln Y_{it} = \alpha + \sum_{z=1}^{4} \beta_z \ln X_{it}^{z} + 0.5 \sum_{w=1}^{4} \sum_{z=1}^{4} \beta_{zz} \ln X_{it}^{w} \ln X_{it}^{z} + \eta_{it} + \varepsilon_{it} \qquad (1)$$

where Y is real output and the inputs X^z are labor, real materials, electricity and the capital stock, η_{it} is a productivity shock known to the firm but unobserved by the

[9] We use the words plant and firm interchangeably, although plants are the unit on which the ENIA survey collects data. Between 1997 and 2003 only 8.3% of Chilean plants are part of a multi-plant firm (Fernandes and Paunov, 2011).

[10] Due to a reorganization of the Chilean territory during our sample period, our final sample includes sector-*comunas* present in the first and last sample years – 1992 and 2004 - as well as in an intermediate sample year 1998.

[11] Statistical tests based on OLS estimates indicate that the translog functional form is more appropriate than the Cobb-Douglas functional form for the Chilean industries.

econometrician and ε_{it} is an independent and identically distributed (i.i.d.) error term capturing unobserved productivity shocks or measurement error. The definition of the output and input variables is provided in the Appendix.

Production function estimation is challenging due to the simultaneity between variable inputs and output both chosen by the firm manager with knowledge of its own productivity η_{it} (Griliches and Mairesse, 1995). Estimating Eq. (1) by OLS would provide biased production function estimates.[12] We estimate Eq. (1) following the LP procedure that builds upon that of Olley and Pakes (1996) but relies on an intermediate input used by all firms, instead of investment, to correct for simultaneity. Since our firm-level TFP estimates are averaged up to obtain sector-location TFP grow it is particularly important to rely on a proxy for unobserved productivity that does not reduce the sample size.[13] We use electricity as the proxy for unobserved productivity.

The LP methodology proceeds in two stages. In the first stage, the coefficients on labor, materials, and interaction terms are estimated by semi-parametric techniques. Assuming that firm demand for electricity increases monotonically with productivity (conditional on the capital stock), that demand can be inverted to express the unobservable productivity as a function of observables: electricity and capital.[14] A nonparametric estimate of this inverse function is used to control for unobservable productivity, removing the simultaneity bias. In the second stage, the coefficients on electricity and capital are obtained by generalized method of moments techniques making

[12] Such bias will likely make firms using relatively more variable inputs appear less productive.

[13] The Olley and Pakes (1996) methodology would drop from the estimating sample firms with zero investment which represent a large proportion of Chilean firms and may be concentrated in specific sector-location cells that would be eliminated from the estimation. If these sector-location cells exhibit systematically different TFP growth and local economic structure, then our estimates could be biased.

[14] This occurs under general conditions on the production function, perfect competition in input markets and perfect competition or some types of imperfect competition in output markets.

the identification assumption that capital adjusts with a lag to productivity.[15] The consistent LP production function coefficient estimates are shown in Table 2.

To implement the second step, we use those production function estimates to compute firm-level TFP estimates as residuals from Eq. (1). We average the firm-level TFP estimates at the sector-*comuna* level using firm-level employment shares as weights, and compute the corresponding growth rate between 1992 and 2004 to obtain sector-*comuna* TFP growth.

3. Empirical Specification and Local Economic Structure Measures

Our empirical specification relating TFP growth with the local economic structure pools across Chilean sector-*comuna* cells and is given by:

$$TFPg_{jrt+T} = \beta_0 + \beta_1 Conc_{jrt} + \beta_2 Div_{jrt} + \beta_3 Comp_{jrt} + \beta_4 AvgS_{jrt} + TFP_{jrt} + I^{j} + \varepsilon_{jrt} \quad (2)$$

where $TFPg_{jrt+T}$ is TFP growth of sector *j* in *comuna r* between 1992 (*t*) and 2004 (*T*), $Conc_{jrt}$, Div_{jrt}, $Comp_{jrt}$, and $AvgS_{jrt}$ are indices capturing local concentration, local diversity, local competition, and local average firm size in 1992, and ε_{jrt} is an i.i.d. residual. TFP_{jrt} is the TFP level of sector *j* in *comuna r* in 1992 that allows to capture possible convergence to the mean for sector-*comuna* cells initially lagging behind. Sector fixed effects I^{j} account for sectoral unobserved factors driving growth between 1992 and 2004 possibly correlated with the local economic structure in 1992: e.g., demand shocks experienced by some sectors and *comunas* that may be correlated with the local economic structure.

[15] We assume that productivity follows a Markov process and capital does not adjust to the unexpected component of current productivity. The reader is referred to LP for technical details.

Our measure of the degree of sector concentration (specialization) in a location follows Glaeser et al. (1992):

$$Conc_{jrt} = \frac{L_{jrt}}{L_{rt}}, \tag{3}$$

where L_{jrt} is total employment in sector *j* and *comuna r* in period *t*, and L_{rt} is total employment in *comuna r* and period *t*. *Higher values* of this index indicate *higher concentration* of the sector in the *comuna*.

The degree of sector diversity in a location is measured by a Hirschman-Herfindhal index following Henderson et al. (1995):

$$Div_{jrt} = \sum_{k \neq j} \left(\frac{L_{krt}}{L_{rt}} \right)^2, \tag{4}$$

where L_{krt} and L_{rt} are defined as above. *Higher values* of this index indicate *lower sector diversity* in the *comuna*.

The degree of sector competition in a location is measured by the inverse of a Hirschman-Herfindhal index as in Combes (2000):

$$Comp_{jrt} = \frac{1}{\sum_{i \in Z} \left(\frac{L_{ijrt}}{L_{jrt}} \right)^2}, \tag{5}$$

where L_{ijrt} is employment of firm *i* operating in sector *j* and *comuna r* in period *t* and L_{jrt} is defined as above. *Higher values* of this index - associated with a more uniform distribution of employment across firms - indicate that the sector exhibits *stronger competition* in the *comuna*. Average firm size in a sector-*comuna* can also be used as a proxy for competition. If a more competitive environment fosters long-run growth, then sectors in locations where the average firm size is smaller should experience faster productivity growth. We measure average size as:

$$AvgS_{jrt} = \frac{L_{jrt}}{n_{jrt}}, \qquad (6)$$

where n_{jrt} is the number of firms in sector *j* and *comuna r* in period *t* and L_{jrt} is defined as above. *Higher values* of this index indicate a *higher average firm size* in the sector and *comuna*. Table 1 reports summary statistics for the local structure indices.

We estimate Eq. (2) using OLS which assumes that the effects of sector-*comuna* shocks to TFP in 1992 do not persist over time. Since there is a 12-year lag between 1992 and 2004, we believe this assumption is not too restrictive. We try to address the potential endogeneity of the annual variation in the agglomeration indices with respect to TFP growth by estimating a reduced form relating initial local economic structure with long-run TFP growth. Another implicit assumption in Eq. (2) is that the parameters of interest are common across sectors (with the exception of the fixed effect).

4. Main Findings

Table 3 reports the results of estimating Eq. (2). Columns (1)-(4) include a single agglomeration index at a time, along with the 1992 TFP level and sector fixed effects. Column (5) reports our baseline specification including simultaneously all the agglomeration indices while columns (6) and (7) include either only the local competition variable or only the average size variable. The results provide evidence of negative MAR externalities, i.e., *comunas* with higher sectoral specialization in 1992 experience lower TFP growth between 1992 and 2004. The estimate of β_1 in column (5) is significant at the 5% confidence level and the magnitude of the effect is economically meaningful. All else constant, an increase in the concentration index from the 1st to the 3rd quartile of its sample distribution would imply a 108% decline in TFP growth in the sector-*comuna* between 1992 and 2004 (equivalent to a 9% annual decline).[16] While the magnitude of this effect is very large, note that the sector-*comuna* TFP growth rates between 1992 and 2004 exhibit a substantial variance: the standard-deviation of TFP growth is 187% while the median is 10.2%.[17] Therefore, such increase in concentration would reduce TFP growth by much less than one standard-deviation. The finding that regional specialization hurts TFP growth in Chile is contrary to the aforementioned agglomeration theories, but is consistent with the empirical evidence for China (Gao, 2004), France (Combes, 2000), Mexico (Hanson, 1998), and the U.S. (Glaeser et al., 1992).

Our results also support the existence of Jacobs externalities i.e., the *comunas* with larger industrial diversity in 1992 exhibit significantly higher TFP growth between 1992 and 2004. The magnitude of β_2 in column (5) implies that an increase in diversity - corresponding to a decline in the index from the 3rd to the 1st quartile of its sample distribution - would result in 149% higher TFP growth between 1992 and 2004 (or 12.4% annually).[18] Again these magnitudes are substantial, but need to be viewed in light of the high variance in TFP growth rates between 1992 and 2004 across sector-*comuna* cells. The finding of Jacobs externalities for Chile is consistent with empirical evidence for the U.S. in Glaeser et al. (1992) and Henderson et al. (1995). Unfortunately our sample does

[16] The implied magnitude over the 12-year sample period is obtained as β_1*(quartile 3 ($Conc_{jrt}$) – quartile 1($Conc_{jrt}$))/median ($TFPg_{jrt+T}$) or replacing by the actual values -0.609*((0.0201–0.0195)/0.102).

[17] These magnitudes are sensible for the historical context given the substantial output and productivity growth experienced across sectors in Chile in the 1990s.

[18] The implied magnitude over the 12-year sample period is obtained as β_2* ((quartile 1 (Div_{jrt}) – quartile 3(Div_{jrt}))/median ($TFPg_{jrt+T}$) or replacing by the actual values -1.003*((0.098–0.250)/0.102).

not cover services. Therefore, some of the estimated benefits of local diversity may be partly attributed to the presence of a diversified set of service sectors in locations where a diversified set of manufacturing sectors is also present.

Our estimates in Table 3 suggest that the initial degree of competition as well as the initial average firm size in the sector-*comuna* have negative but weak effects on TFP growth in Chile. Columns (6) and (7) show that this is obtained even when only one of these proxies for competition is included. The weakness in competition effects on TFP growth is not surprising given the theoretical ambiguity discussed in Section 1. Finally, the strong negative effect of the initial TFP level in the sector-*comuna* on subsequent TFP growth indicates an important degree of TFP convergence over the long-run.

One concern with Table 3 is that the effects of agglomeration externalities proxy for other characteristics of sector-*comuna* cells. Although the specifications control for the initial sector-*comuna* TFP level, other sector-*comuna* characteristics such as the size of the local market, may bias our estimates. Table 4 presents the results from estimating Eq. (2) including additional sector-*comuna* controls as of 1992: total employment in column (1), total output in column (2), total capital in column (3), total intermediate inputs in column (4), and total skilled labor in column (5). The significant negative MAR externalities and the positive Jacobs externalities on TFP growth remain. The weak effects of the competition index remain while average firm size has a significant negative effect on TFP growth in column (3).

5. Sensitivity Analysis

Our main findings for Chile suggest that the source of local agglomeration externalities is sectoral diversity. That is, while knowledge spillovers across firms in a given sector may hurt industrial TFP growth in a location, the cross-fertilization of ideas across firms in different sectors promotes industrial TFP growth in the location. To check the robustness of our main findings in column (5) of Table 3, we conduct several sensitivity tests, reported in Table 4. First, we exclude from the sample the petroleum and tobacco sectors which are characterized by a small number of firms concentrated in a small number of *comunas* and by a large degree of state control and for which TFP growth may not be linked to market-related dynamic externalities. Column (1) of Table 5 shows that our findings are robust to those sectors' exclusion.

A possible concern is that dynamic agglomeration externalities at the local level differ across sectors. For example, knowledge spillovers may be more important in sectors with rapidly changing technologies. While much of the literature on European manufacturing focuses on the role of networks and clusters in fostering the viability of small firms in traditional sectors, it is possible that less traditional sectors benefit more from spillovers. In columns (2) and (3) of Table 5 we allow the intensity of the agglomeration externalities to differ across high- and low-tech sectors, defined according to the OECD classification (see the appendix). The results for the high-tech sample are weaker than those for the low-tech or the full samples due to its smaller size, but the effects of concentration and diversity are qualitatively similar across the two types of sectors.

In column (4) of Table 5, we estimate Eq. (2) considering a smaller sample including only sector-*comuna* cells whose TFP growth between 1992 and 2004 is larger than the 1st percentile and smaller than the 99th percentile of the TFP growth distribution. The results on concentration and diversity are qualitatively maintained.

Since TFP growth for a sector-*comuna* cell is calculated as the growth between 1992 and 2004 of sector-*comuna* TFP levels obtained as the average of the TFP of firms in that cell, more precise TFP estimates are expected for cells including larger numbers of firms. In column (5) of Table 3 we present the results from estimating Eq. (2) using weighted least squares, where each cell is weighted by its number of firms. Our findings are maintained though the negative effect of diversity is weaker.

In columns (6)-(7) of Table 5, we examine whether our findings are driven by the measurement of our dependent variable. In column (6) we obtain sector-*comuna* TFP as the simple average of firm-level TFP estimates while in column (7) we obtain sector-*comuna* TFP as the employment-weighted average of firm-level TFP estimates based on OLS translog production function coefficients. The significant effects of concentration and diversity as well as the weak effects of competition and average size are maintained.

The reduced form reported in Eq. (2) may suffer from an omitted variables problem related with geographical location: time-invariant location characteristics such as geography, natural resources, or access to markets may simultaneously affect both sector-location TFP growth and local economic structure. Table 6 reports the findings from adding location fixed effects at various disaggregation levels to Eq. (2). Column (1) adds region fixed effects while columns (2) and (3) add, respectively, province and *comuna* fixed effects. The effects of concentration and diversity are qualitatively maintained when time-invariant location characteristics are controlled for though their significance weakens in columns (2)-(3). In column (4) we estimate Eq. (2) excluding from the sample the smallest provinces (measured by total population) which may be less prone to benefit from agglomeration externalities. We obtain similar results to those in our baseline specification.

To analyze the extent to which our findings based on TFP growth differ from those based on employment growth, Table 7 shows the results of estimating Eq. (2) using sector-*comuna* employment growth between 1992 and 2004 as dependent variable. The estimates in column (5) suggest no evidence of MAR externalities, evidence of negative Jacobs externalities, no effect of competition, and a negative effect of initial average firm size on employment growth. There is evidence of convergence, i.e., sector-*comuna* cells with lower employment levels in 1992 exhibit higher employment growth subsequently. As explained in Section 1 there are several reasons why employment and productivity growth do not necessarily covary. We interpret the findings in Table 7 as showing the importance of constructing careful TFP estimates and the corresponding growth rates - instead of employment growth rates - to assess the long-run effect of the local economic structure on growth.

In Table 8, we delve further into the evidence of Jacobs externalities by examining the extent to which sector-*comuna* TFP growth is related to vertical linkages, namely the presence of firms in upstream (potential suppliers) or downstream (potential buyers) sectors. Suppliers and buyers are possible conduits for knowledge spillovers through informal contacts or the mobility of skilled labor. For example, a firm that incorporates new higher quality inputs into its final product may reap some of the benefits from its suppliers' knowledge. Similarly, incremental improvements in process technology can result from knowledge sharing between suppliers and downstream firms.

Finally, buyer firms may foster productivity in their suppliers through increased training of the workforce, quality control, inventory management, technical assistance, or product development (see e.g., Amiti and Cameron, 2007; Javorcik, 2004; Blalock and Gertler, 2007). We estimate a variant of Eq. (2) where the diversity index given by Eq. (3) is calculated separately for suppliers and non-suppliers (column (1)) or for buyers and non-buyers (column (2)). We identify suppliers and buyers based on the 1986 Chilean input-output matrix.[19] The estimates in Table 8 show significantly negative MAR externalities and no effects of competition nor average firm size. Regarding diversity, columns (1) and (2) show that the diversity of non-suppliers and the diversity of non-buyers are the most important types of sectoral diversity for TFP growth. These findings go against our priors from the agglomeration literature and the findings in Amiti and Cameron (2007). While our input-output linkages measures are imperfect - because they are based on a national input-output table rather than regional input-output tables - our findings suggest that the sectoral diversity unrelated to supplier and clients is what matters most for TFP growth. Such agglomeration externalities could happen through the exchange of ideas and workers through labor pooling, knowledge spillovers, or the availability of financing.

Evaluating the impact of agglomeration indices in 1992 on long-run TFP growth between 1992 and 2004 across Chilean sector-*comuna* cells deals away with reverse causality problems, but the 1992-2004 period may be too long to identify certain types of

[19] The implicit assumption is that input-output relations hold across locations. For any 3-digit sector *j* we calculate the share that each 3-digit sector represents in its intermediate input usage, we rank those shares in ascending order and compute the cumulative sum of shares. 'Suppliers' are the 3-digit sectors whose cumulative sum of shares in total intermediate inputs is closest (from above) to 90%. 'Non-suppliers' are all other 3-digit sectors. Similarly, for any 3-digit sector j we calculate the share that each 3-digit sector represents in its sales, we rank those shares in ascending order and compute a cumulative sum of shares. 'Buyers' are the 3-digit sectors whose cumulative sum of shares in output sales is closest (from above) to 90%. 'Non-buyers' are all other 3-digit sectors. For any given sector *j*, sector *j* itself is always included as part of the set of supplier sectors as well as of the set of buyer sectors. However sector *j* is excluded by definition from the calculation of the diversity index.

dynamic externalities. Moreover, some externalities could have been relevant in the medium-run but vanish over the long-run. Table 8 presents the results of estimating Eq. (2) considering three sub-periods for TFP growth rates: 1992-1996, 1996-2000, and 2000-2004. For each sub-period, TFP growth is affected by agglomeration externalities indices measured in the first year of the sub-period. The results are again suggestive of negative MAR externalities and positive Jacobs externalities. The effect of competition is still weak but average firm size has a significant positive effect on TFP growth.

6. Conclusion

This paper examines how the local economic structure affected manufacturing productivity growth in Chile between 1992 and 2004. For a given sector, we examine whether locations with a greater concentration of that economic activity performed better in the long-run than locations where economic activity was more diversified. We explore a panel of firm-level data to compute TFP estimates following the semi-parametric methodology of Levinsohn and Petrin (2003) which corrects for the possible simultaneity between input choices and productivity.

Our findings strongly suggest that Chilean *comunas* with greater concentration of a certain sector have not experienced faster TFP growth. Our findings are more supportive of the view that regional diversity in the sectoral composition is associated with faster long-run growth. These findings are robust to a variety of sensitivity checks, such as the control for sector-location characteristics, possibly related to long-run TFP growth and to the local economic structure. Our findings are in line with those by

Brülhart and Mathys (2008) for manufacturing growth in European regions, but are not explained by the proximity of suppliers and/or clients.

Our findings have important policy implications for the design of urban development policies. By showing that locations with a more diverse set of industrial activities exhibit faster TFP growth, our evidence does not support the formation of homogeneous but rather of heterogeneous industrial clusters.

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Appendix

A. Details on Dataset and Production Function Estimation

From 1992 to 2002, plants in the ENIA are characterized by a unique plant identifier that allows the linkage of plants over time to generate a panel. In 2003, the plant identifier changed. However, we have access to a different version of the datasets for 2001 and 2002 that include the new post-2003 identifier. A correspondence between the old and the new plant identifier is established based on a merger of the two datasets according to a large (more than 100) number of survey variables. In this way, a panel of plants from 1992 to 2004 was created. For some cases where the correspondence between the old and the new plant identifier was ambiguous and unclear, we keep the plant with the old identifier and the plant with the new identifier as separate plants. The Chilean dataset has been used extensively in research and is judged to be of high quality. Thus, only minor data cleaning procedures are applied. First, we exclude from the analysis plants with missing identifiers, output or input variables, or sector affiliation. Second, we impute output and inputs to correct for non-reporting by a plant in a single year (occurring in fewer than 30 plant-year observations). Third, we exclude from the analysis plants whose output growth is larger than (smaller than) 400% and those whose output growth ranges between 100% and 300% (-300% and -100%) but is not accompanied by corresponding high (low) growth rates of inputs. The sample includes some plants with discontinuous data over the sample period. For those plants, we consider only the observations across consecutive years for which yearly growth rates can be computed.

Real output is measured as firm sales deflated by a 3-digit ISIC output price deflator constructed from data provided by the National Statistical Institute (INE) of Chile. INE reports indices of production quantity and indices of sales for each 3-digit industry between 1992 and 2004. Since sales=quantity*price, we can derive a price deflator for each 3-digit industry. Real materials is measured as material expenditures deflated by a 3-digit material inputs deflator which is obtained by combining the 3-digit ISIC output price deflator with input-output tables for 1986 and 1996. Real output and real materials are expressed in thousands of constant 1992 pesos.

Labor is measured as the sum of owners, executives, professionals, administrative workers, direct and indirect production workers, and home-based workers.

Electricity is measured by the quantity of electricity consumed expressed in thousands of kilowatts.

Capital is constructed using the perpetual inventory formula to cumulate investment flows. The ENIA collects information on investment flows and on book values for four types of capital goods: land, buildings, machinery and equipment, and transport equipment. We apply the following perpetual inventory method (PIM) formula to each type of capital goods *m*: $K_{it}^{m} = (1-\delta^{m})K_{it-1}^{m} + I_{it}^{m}$, where I_{it}^{m} are deflated net investment flows (purchases of new or used capital goods minus sales of capital goods) and δ^{m} is the annual depreciation rate. All four types of capital are transformed into constant 1992 pesos using an aggregate investment deflator constructed from World Development Indicators data on current and constant values of gross fixed capital formation in Chile between 1992 and 2004. An initial value for the capital stock which is necessary to apply the PIM formula is given by the book value of each of the four types of capital in the first year of plant presence in the sample. Whenever information on the book value is available only in a subsequent year, we back out that value using the investment deflator and taking into account the corresponding depreciation rate all the way to the plant's first year of presence in the sample. Since detailed studies of depreciation rates in Chile are unavailable, we use the depreciation rates proposed by Pombo (1999) who studied the same type of capital goods in Colombia. Specifically, the depreciation rates used are 3% for buildings, 7.7% for machinery and equipment, and 11.9% for transport equipment. Land is assumed not to depreciate. However, we note that our findings are robust to the use of alternative depreciation rates to construct the capital stocks. In order to obtain the firm's total capital stock we simply sum the capital stocks of land, buildings, machinery and equipment, and of transport equipment.

B. High-Tech and Low-Tech Sectors

We follow the OECD classification of industries according to their R&D intensity into high-tech industries (high-tech and medium-high-tech in that classification) and low-tech industries. High-tech industries are 351, 352, 353, 354, 355, 356, 381, 382, 383, 384, 385 in the ISIC 3-digit classification.

Table 1: Summary Statistics

	Number of Firms	TFP growth 1992-2004	Concentration Index 1992	Diversity Index 1992	Competition Index 1992	Avg. Firm Size 1992
	(1)	(2)	(3)	(4)	(5)	(6)
Statistics						
Mean	5.1	0.0	0.2	0.2	2.8	98
Median	3.0	0.1	0.1	0.1	1.9	52
Standard Deviation	7.8	1.9	0.3	0.2	3.2	179
Minimum	1.0	-12.5	0.0	0.0	1.0	10
Maximum	135.0	10.8	1.0	1.0	31.8	3663

Note: Table reports summary statistics based on the sample of sector-*comuna* cells used in the econometric analysis.

Table 2: Translog Production Function Estimates Following Levinsohn and Petrin (2003)

	Food (ISIC 31)	Textiles and Apparel (ISIC 32)	Wood and Furniture (ISIC 33)	Paper and Printing (ISIC 34)	Chemicals (ISIC 35)	Nonmetallic Minerals (ISIC 36)	Basic Metals (ISIC 37)	Machinery (ISIC 38)	Other Manufacturing (ISIC 39)
Labor	0.211	0.755***	0.677***	0.583*	0.362**	0.813***	0.454	0.973***	2.242***
	(0.138)	(0.165)	(0.168)	(0.324)	(0.159)	(0.211)	(0.491)	(0.158)	(0.561)
Real Materials	0.637***	-0.011	0.107	0.464	0.097	-0.069	0.036	-0.114	-1.079***
	(0.173)	(0.168)	(0.133)	(0.321)	(0.113)	(0.156)	(0.240)	(0.116)	(0.373)
Electricity	0.270	0.010	0.170	0.010*	0.010	0.980***	0.100	0.270	0.900**
	(0.188)	(0.194)	(0.216)	(0.189)	(0.350)	(0.385)	(0.360)	(0.296)	(0.449)
Capital	0.300	0.980***	0.900***	0.980***	0.980***	0.440	0.010***	0.010	0.010
	(0.341)	(0.389)	(0.300)	(0.340)	(0.421)	(0.365)	(0.402)	(0.345)	(0.444)
Labor * Labor	0.013*	0.047***	0.026***	0.012	0.043*	0.038***	0.140**	0.047***	-0.017
	(0.007)	(0.009)	(0.010)	(0.034)	(0.023)	(0.014)	(0.065)	(0.012)	(0.062)
Real Materials * Real Materials	0.019	0.048***	0.055***	0.033	0.058***	0.072***	0.067***	0.054***	0.069***
	(0.012)	(0.011)	(0.009)	(0.027)	(0.008)	(0.008)	(0.015)	(0.007)	(0.025)
Electricity * Electricity	0.000	0.001***	0.007	-0.015	0.000***	0.000***	-0.009	0.000	0.000***
	(0.008)	(0.007)	(0.019)	(0.024)	(0.019)	(0.006)	(0.048)	(0.012)	(0.095)
Capital * Capital	-0.002	0.000***	-0.007	0.000	0.023***	0.000***	0.094***	0.038*	0.000***
	(0.012)	(0.007)	(0.028)	(0.015)	(0.007)	(0.020)	(0.096)	(0.022)	(0.058)
Labor * Real Materials	-0.015	-0.063***	-0.076***	-0.081**	0.006	-0.089***	-0.012	-0.091***	-0.220***
	(0.015)	(0.019)	(0.018)	(0.040)	(0.026)	(0.020)	(0.038)	(0.019)	(0.057)
Labor * Electricity	-0.019	0.006	-0.003	0.022	-0.029***	0.006	-0.080	0.000***	0.094***
	(0.016)	(0.013)	(0.013)	(0.026)	(0.010)	(0.016)	(0.052)	(0.011)	(0.046)
Labor * Capital	0.008	-0.012	0.022*	0.034*	-0.034**	0.012	-0.056	0.003***	0.027
	(0.009)	(0.010)	(0.012)	(0.020)	(0.017)	(0.016)	(0.067)	(0.014)	(0.046)
Real Materials * Electricity	0.003	-0.010	-0.014	0.011	-0.033***	-0.053***	-0.052***	-0.018*	-0.007
	(0.014)	(0.011)	(0.011)	(0.017)	(0.009)	(0.014)	(0.019)	(0.010)	(0.033)
Real Materials * Capital	-0.025***	-0.018*	-0.030***	-0.031	-0.057***	-0.037***	-0.066***	-0.011	0.070*
	(0.009)	(0.010)	(0.010)	(0.024)	(0.010)	(0.014)	(0.024)	(0.009)	(0.039)
Electricity * Capital	0.000	0.056	0.000	0.026	0.100	0.000***	0.000***	0.001	-0.092
	(0.013)	(0.039)	(0.018)	(0.030)	(0.067)	(0.054)	(0.093)	(0.037)	(0.168)
Observations	16365	8321	5140	3302	6269	2206	777	8689	663

Notes: Bootstrapped standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is log of firm real output and all inputs are in logs.

Table 3: Dynamic Externalities and Long-Run Productivity Growth in Manufacturing: Baseline Specification

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Concentration Index in Sector-*Comuna*	-0.359				-0.609	-0.687	-0.567
	[0.262]				[0.295]**	[0.290]**	[0.291]*
Diversity Index in Sector-*Comuna*		-0.561			-1.003	-0.969	-0.912
		[0.328]*			[0.372]***	[0.371]***	[0.358]**
Competition Index in Sector-*Comuna*			-0.0003		-0.018	-0.016	
			[0.019]		[0.020]	[0.020]	
Avg. Firm Size in Sector-*Comuna*				-0.001	-0.001		-0.001
				[0.000]	[0.000]		[0.000]
Initial TFP of Sector-*Comuna*	-0.383	-0.37	-0.375	-0.394	-0.397	-0.381	-0.397
	[0.033]***	[0.033]***	[0.033]***	[0.035]***	[0.035]***	[0.033]***	[0.035]***
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.23	0.23	0.23	0.23	0.24	0.24	0.24
Observations	853	853	853	853	853	853	853

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the sector-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna* , diversity is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* based on employment, competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna* based on employment, avg. firm size is the average size of firms (measured by employment) in the sector-*comuna* and initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level.

Table 4: Dynamic Externalities and Long-Run Productivity Growth in Manufacturing: Including Sector-*Comuna* Controls

	(1)	(2)	(3)	(4)	(5)
Concentration Index in Sector-*Comuna*	-0.602	-0.625	-0.643	-0.644	-0.705
	[0.2947]**	[0.2962]**	[0.2955]**	[0.2972]**	[0.2965]**
Diversity Index in Sector-*Comuna*	-1.043	-0.998	-1.041	-1.027	-1.106
	[0.3729]***	[0.3721]***	[0.3725]***	[0.3736]***	[0.3738]***
Competition Index in Sector-*Comuna*	0.000	-0.021	-0.022	-0.023	0.002
	[0.0244]	[0.0205]	[0.0203]	[0.0205]	[0.0233]
Avg. Firm Size in Sector-*Comuna*	-0.0004	-0.0006	-0.0007	-0.0007	-0.0007
	[0.0004]	[0.0004]	[0.0004]*	[0.0004]*	[0.0004]
Initial TFP of Sector-*Comuna*	-0.407	-0.395	-0.392	-0.393	-0.402
	[0.0356]***	[0.0352]***	[0.0351]***	[0.0357]***	[0.0365]***
Total Employment of Sector-*Comuna*	Yes	No	No	No	No
Total Output of Sector-*Comuna*	No	Yes	No	No	No
Total Capital of Sector-*Comuna*	No	No	Yes	Yes	Yes
Total Intermediate Inputs of Sector-*Comuna*	No	No	No	Yes	Yes
Total Skilled Labor of Sector-*Comuna*	No	No	No	No	Yes
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes
R-Squared	0.24	0.24	0.24	0.24	0.25
Observations	853	853	853	853	853

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the region-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna* , diversity is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* , competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna* , avg. firm size is the average size of firms (measured by employment) in the sector-*comuna*, and the initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level. Columns (1) to (5) add different sector-*comuna* characteristics to the baseline specification reported in Eq. (2) of the text.

Table 5: Dynamic Externalities and Long-Run Productivity Growth in Manufacturing: Robustness

	Sample Excluding Petroleum and Tobacco	Sample of High Tech Sectors	Sample of Low Tech Sectors	Sample Excluding Top and Bottom 1% Outliers	Weighted Least Squares	No Weights Average TFP at Sector-*Comuna* Level	TFP Estimates using OLS Translog Prod. Fct. Coeff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Concentration Index in Sector-*Comuna*	-0.615	-1.516	-0.439	-0.4539	-0.6793	-0.5111	-0.207
	[0.294]**	[1.876]	[0.249]*	[0.2390]*	[0.2729]**	[0.2636]*	[0.107]*
Diversity Index in Sector-*Comuna*	-0.995	-2.25	-0.428	-0.8616	-0.5958	-0.9739	-0.287
	[0.372]***	[0.927]**	[0.353]	[0.3035]***	[0.4700]	[0.3328]***	[0.135]**
Competition Index in Sector-*Comuna*	-0.019	-0.017	-0.02	-0.0084	-0.0024	0.0158	0.005
	[0.020]	[0.048]	[0.019]	[0.0163]	[0.0087]	[0.0180]	[0.007]
Avg. Firm Size in Sector-*Comuna*	-0.0010	-0.002	-0.001	-0.0001	-0.0006	-0.0005	0.0000
	[0.000]	[0.002]	[0.000]*	[0.0003]	[0.0006]	[0.0003]	[0.000]
Initial TFP of Sector-*Comuna*	-0.401	-0.358	-0.512	-0.2473	-0.395	-0.3757	-1.110
	[0.035]***	[0.071]***	[0.043]***	[0.0305]***	[0.0383]***	[0.0348]***	[0.052]***
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.24	0.23	0.23	0.2	0.27	0.21	0.38
Observations	847	263	590	837	853	853	853

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the sector-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna*, diversity is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* based on employment, competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna* based on employment, avg. firm size is the average size of firms (measured by employment) in the sector-*comuna* and initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level. Column (2) includes only the high tech sectors (chemicals and machinery) and column (3) includes only the low tech sectors (food, textiles, wood, paper, glass, basic metals and other manufacturing sectors). Column (4) uses only sector-comuna cells with TFP growth rates between the 1st and 99th percentile of distribution of TFP growth rates. Column (5) estimates Eq. (2) in the text using weighted least squares. Column (6) does not use weights when averaging firm-level TFP to the sector-comuna level. Column (7) uses firm-level TFP measures obtained from a Translog production function using OLS (then averaged to sector-comuna level using employment weights).

Table 6: Dynamic Externalities and Long-Run Productivity Growth in Manufacturing: Robustness to Regional Effects

				Sample Excluding Smallest Provinces
	(1)	(2)	(3)	(4)
Concentration Index in Sector-*Comuna*	-0.714	-0.795	-2.222	-0.661
	[0.3301]**	[0.3856]**	[1.6835]	[0.3067]**
Diversity Index in Sector-*Comuna*	-1.063	-1.105	-2.553	-1.010
	[0.4223]**	[0.4994]**	[1.9124]	[0.3771]***
Competition Index in Sector-*Comuna*	-0.016	-0.014	-0.026	-0.017
	[0.0203]	[0.0209]	[0.0279]	[0.0204]
Avg. Firm Size in Sector-*Comuna*	-0.001	-0.001	0.000	-0.001
	[0.0004]	[0.0004]	[0.0005]	[0.0004]
Initial TFP of Sector-*Comuna*	-0.403	-0.403	-0.447	-0.399
	[0.0353]***	[0.0362]***	[0.0433]***	[0.0353]***
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes
Region Fixed Effects Included?	Yes	No	No	No
Province Fixed Effects Included?	No	Yes	No	No
Comuna Fixed Effects Included?	No	No	Yes	No
R-Squared	0.25	0.26	0.32	0.24
Observations	853	853	853	837

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the sector-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna*, diversity is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* based on employment, competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna* based on employment, avg. firm size is the average size of firms (measured by employment) in the sector-*comuna*, and initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level.

Table 7: Dynamic Externalities and the Long-Run Employment Growth in Manufacturing

	(1)	(2)	(3)	(4)	(5)
Concentration Index in Sector-*Comuna*	-0.3587				0.0708
	[0.1680]**				[0.1877]
Diversity Index in Sector-*Comuna*		1.1626			1.1305
		[0.2153]***			[0.2383]***
Competition Index in Sector-*Comuna*			-0.013		-0.0162
			[0.0148]		[0.0155]
Avg. Firm Size in Sector-*Comuna*				-0.0006	-0.0006
				[0.0002]***	[0.0002]**
Initial TFP of Sector-*Comuna*	-0.0003	-0.0002	-0.0003	-0.0002	-0.0001
	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]***	[0.0001]**
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes
R-Squared	0.13	0.16	0.13	0.13	0.16
Observations	853	853	853	853	853

Notes: Standard errors in parenthesis. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is employment growth in the sector-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna*, diversity is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* based on employment, competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna* based on employment, avg. firm size is the average size of firms (measured by employment) in the sector-*comuna* and initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level.

Table 8: Dynamic Externalities and Long-Run Productivity Growth in Manufacturing: Diversity Suppliers and Buyers

	Diversity Suppliers	Diversity Buyers
	(1)	(2)
Concentration Index in Sector-*Comuna*	-0.609	-0.718
	[0.2950]**	[0.2986]**
Diversity Index Suppliers in Sector-*Comuna*	-0.949	
	[0.6823]	
Diversity Index Non-Suppliers in Sector-*Comun*	-1.014	
	[0.3890]***	
Diversity Index Buyers in Sector-*Comuna*		-0.189
		[0.5321]
Diversity Index Non-Buyers in Sector-*Comuna*		-1.445
		[0.4249]***
Competition Index in Sector-*Comuna*	-0.018	-0.017
	[0.0201]	[0.0200]
Avg. Firm Size in Sector-*Comuna*	-0.001	-0.001
	[0.0004]	[0.0004]
Initial TFP of Sector-*Comuna*	-0.398	-0.403
	[0.0350]***	[0.0350]***
Sector Fixed Effects Included?	Yes	Yes
R-Squared	0.24	0.24
Observations	853	853

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the sector-*comuna* between 1992 and 2004. Concentration is the sector's employment share in the *comuna*, diversity index (non)suppliers is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* constructed only for the sector's (non)suppliers, diversity index (non)buyers is the Hirschman-Herfindhal index of sectoral diversity in the *comuna* constructed only for the sector's (non)buyers, competition is the Hirschman-Herfindhal index of sectoral competition in the *comuna*, avg. firm size is the average size of firms (measured by employment) in the sector-*comuna* and the initial TFP is the TFP level of the sector-*comuna* in 1992. Sector fixed effects included are at the 3-digit ISIC level.

Table 9: Dynamic Externalities and Medium-Run Productivity Growth in Manufacturing

	(1)	(2)	(3)	(4)	(5)
Concentration Index in Sector-*Comuna*	-0.174	-0.157	-0.154	-0.045	0.794
	[0.1561]	[0.1542]	[0.1755]	[0.2142]	[0.4976]
Diversity Index in Sector-*Comuna*	-0.535	-0.468	-0.372	-0.248	0.613
	[0.2227]**	[0.2202]**	[0.2503]	[0.3024]	[0.5837]
Competition Index in Sector-*Comuna*	-0.007	-0.0101	-0.010	-0.0108	-0.0257
	[0.0098]	[0.0097]	[0.0098]	[0.0100]	[0.0122]**
Avg. Firm Size in Sector-*Comuna*	0.0003	0.0004	0.0004	0.000	0.000
	[0.0002]*	[0.0002]*	[0.0002]*	[0.0002]*	[0.0003]
Initial TFP of Sector-*Comuna*	-0.834	-0.855	-0.875	-0.875	-0.946
	[0.0873]***	[0.0894]***	[0.0902]***	[0.0918]***	[0.0979]***
Sector Fixed Effects Included?	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects Included?	No	Yes	Yes	Yes	Yes
Region Fixed Effects Included?	No	No	Yes	No	No
Province Fixed Effects Included?	No	No	No	Yes	No
Comuna Fixed Effects Included?	No	No	No	No	Yes
R-Squared	0.07	0.09	0.1	0.1	0.12
Observations	2,071	2,071	2,071	2,071	2,071

Notes: Standard errors in parentheses. *** significant at 99%; ** significant at 95%; * significant at 90%. Dependent variable is TFP growth in the sector-region in each of the 4-year periods: 1992-1996, 1996-2000, and 2000-2004. Concentration is the sector's employment share in the comuna, diversity is the Hirschman-Herfindhal index of sectoral diversity in the comuna based on employment, competition is the Hirschman-Herfindhal index of sectoral competition in the comuna based on employment, avg. firm size is the average size of the firm in the sector-comuna and initial TFP is the TFP level of the sector-comuna in the first year of the 4-year periods. Sector fixed effects included are at the 3-digit ISIC level. Columns (2)-(5) include also fixed effects for the 4-year periods.