We study the cyclical behavior of labor productivity in eighty industries of the Chilean manufacturing sector in the 1979-2001 period. We find that labor productivity at the sector-level is procyclical but it is a-cyclical when using aggregate data. We provide an analytical and empirical explanation for this divergence. We also use an econometric model to quantify the determinants of productivity. The results indicate that technology shocks account for one half of productivity growth, thus supporting the supply shocks hypothesis as the main source of business cycles in Chile. The other 50% of the productivity changes is explained by reallocation of resources from less to more productive sectors as well as the presence of increasing returns. Variations in factor utilization were insignificant.

**JEL:** E32, J24, C1

**Keywords:** Productivity, Procyclical, Manufacturing, Aggregation Bias.

1. **INTRODUCTION**

It is now generally accepted that aggregate labor productivity tends to rise during booms and fall during recessions\(^1\). This fact is at odds with classical economic theory which suggests that labor productivity should be countercyclical

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as a result of the law of diminishing returns to factors. Traditional explanations for this puzzle are procyclical technology shocks (e.g., Kydland and Prescott, 1982), imperfect competition and increasing returns (e.g., Hall, 1990), and variable capital utilization and labor hoarding (e.g., Burnside et al., 1993).

An important limitation of this literature is its reliance on aggregate data. While useful, aggregate data are limited by biases arising from the construction of aggregate series of productivity, capacity utilization, and resource relocation. As shown in this paper, the composition of aggregate productivity indexes can severely distort the measurement of the cyclical properties of productivity. A second limitation is that most of the evidence is only available for developed economies. Data from developing economies—which remains largely unexplored—could provide important insights to understand the response of firms to shocks, given that economic cycles tend to be more pronounced in emerging economies.

In this paper we use data from the Chilean manufacturing firms for the 1979-2001 period to study the cyclical behavior of labor productivity at the sector level, its determinants, and its relationship with economic activity. The Chilean case is interesting because its economy is very dynamic, small for international standards but quite open to foreign markets, and largely free of preferential tax treatments for selected industries. The economy has grown at impressive rates in the last two decades while, at the same time, it has been subject to significant external shocks. Consequently, firms have had to continuously adjust to a changing environment. Studies using macroeconomic data suggest that the impressive annual growth rate of 5% in the last 20 years is largely the result of technological innovation and a dramatic change in capital-labor ratios (Bergoeing et al., 2002). At the microeconomic level, Camhi et al. (1997) provide evidence that productivity increased in the 1979-1994 period as a result of the entry of new firms that were more efficient than incumbents.

A simple model is developed in section 2 to provide a framework for the analysis, embedding five alternative hypotheses on the correlation between labor productivity and economic cycles. In section 3 we encompass these hypotheses in a testable specification, which takes into account the nature of the data, the need to control for changes in the use of intermediate goods, and the implications of aggregating firm-level productivity. Section 4 describes the structure of the data and presents evidence of procyclical labor productivity at the aggregate level. However, we find no evidence of procyclicality when using the aggregate data of the ENIA firms; correlation is 0.06. When studying this correlation industry by industry we found that most sectors exhibit significant procyclical productivity; the simple average of the individual correlations is around 0.64. Section 5 reconciles this apparently conflicting individual and aggregate evidence both from an analytical and empirical point of view. It documents that aggregation

biases arising in the construction of the aggregate productivity series distort the cross-industry correlation between cycles in labor productivity and economic activity. This reflects the substantial heterogeneity not only in the productivity structure of ENIA firms but also in the timing of the cycles of the different industries. Productivity is procyclical across industries but the cyclical phases of the industries are significantly different between each other, leading to an aggregate a-cyclical productivity.

Section 6 tests the determinants of productivity in the Chilean industry using an econometric model that allows us to quantify the relative contribution of the above mentioned explanations of procyclical productivity. The results indicate that technology shocks account for around one half of productivity changes in the 1979-2001 period, thus supporting the supply shocks hypothesis as the main source of business cycles in Chile. The other half of the productivity changes are explained mainly by the exploitation of increasing returns in the 1980s and by reallocation effects between industries of different productivity in the 1990s. Variations in the utilization rates of inputs tend to play a less significant contribution to changes in productivity in the long run. Section 7 collects the main conclusions.

2. ALTERNATIVE EXPLANATIONS FOR LABOR PRODUCTIVITY CYCLES

We develop a stylized, flexible model of market interaction to derive our average labor productivity measure and its correlation with business cycles. The starting point of the analysis is the following generalized function:

\[ Y_{it} = A_{it}F(u_{it}K_{it},e_{it}L_{it})Y_{it}^{\nu} \]

where \( F \) is a generic production function, \( Y_{it} \) is the real value added of the firm \( i \) at time \( t \), \( A_{it} \) is a strictly positive level of technology, \( K_{it} \) is the stock of capital and \( u_{it} \) its utilization rate, \( L_{it} \) represents total hours worked and \( e_{it} \) is the effort per unit of work, and \( Y_{i} \) is the aggregate output of the industry in which the firm operates. Utilization and effort variables are in the [0,1] interval. Parameter \( \nu \) in the internal [0,1] denotes the existence of external effects, as described below. Assume that each firm faces a demand curve with constant price-elasticity. The inverse demand curve is:

\[ P_{it} = D_{it}e^{\eta_{it}} Y_{it}^{-\phi} \]

where \( P_{it} \) is the price of the good produced by the firm, \( D_{it} \) is a parameter that captures idiosyncratic features in the demand, \( \eta_{it} \) is a stochastic i.i.d. shock that affects all firms, and \( \phi \) is a constant that allows for either competitive (\( \phi = 1 \)) or imperfectly competitive behavior (\( \phi < 1 \)).
Technology evolves according to the following law of motion:

\[ A_t = (1 - \rho) A_{t-1} + \rho A_{t-1} + \varepsilon_t \]

where \( \varepsilon_t \) is a stochastic i.i.d. technology shock and \( \rho \) is a constant with values between 0 and 1. These three equations describe the structure of the economy. We assume equilibrium at all times.

Productivity cyclicality is assessed using the correlation between cyclical measures of output and average labor productivity. When such correlation is positive, labor productivity is said to be procyclical; likewise, when it is negative productivity is dubbed countercyclical. Cyclical fluctuations in labor productivity arise as a result of supply and demand shocks. Consequently, we study the sign of \( \frac{dY_t}{d\tau_t} \) (where \( \tau_t \) is either a supply or a demand shock) and its correlation to output under alternative assumptions about the structure of the economy. There are five cases of interest, which we discuss below, stressing either supply side elements (as in the business cycle literature) or demand-driven elements, as in classical economics or in the more recent models of factor hoarding and of external effects affecting firm’s production and productivity.

**Traditional Model.** This model assumes that there are no external effects, unused capital, or idle labor in the firm. It also assumes that technology is stationary. Consequently, the production function becomes \( Y_t = A_t F(K_t, L_t) \) and the response of productivity to demand shocks (\( \eta_t \)) is:

\[ \frac{dY_t}{d\eta_t} = A_t \left( \frac{L_t F_{t}^{L} - F_t}{L_t^2} \right) \frac{\partial L_t}{\partial \eta_t} \leq 0 \]

where \( F_{t}^{L} = \frac{\partial L_t}{\partial Y_t} \) denotes the derivative of the production function with respect to labor. Equation (4) is usually negative because \( \frac{\partial L_t}{\partial \eta_t} \) is positive and the term in the parenthesis is negative since \( L_t F_{t}^{L} \) is the equilibrium payment to labor. Therefore, average labor productivity is countercyclical. The intuition is that firms do not change their production technology and, therefore, in the short run demand shocks induce a movement along the (decreasing) marginal productivity curve.

**Technology shocks.** This explanation –as proposed in the real business cycles literature pioneered by Kydland and Prescott (1982)– focuses on technology shocks (\( \varepsilon_t \)) as the driving force of economic cycles. Assume that there are no external effects, unused capital, or idle labor in the firm. In such case, the production function is similar to that in the traditional model, except that productivity is now time-varying. Average labor productivity becomes procyclical since:
Labor hoarding. Following Baily et al. (2001), assume that there are no external effects, technology shocks, or unused capital but labor comprises time allocated to production, \( q_{it} \), and time dedicated to maintenance and training, \( m_{it} \). Naturally, \( q_{it} + m_{it} = L_{it} \). The component \( m_{it} \) is thought of as producing human capital and/or providing maintenance to the stock of capital that, otherwise, should be added to the capital input measure or included as a new factor in the production function. From equation (1) \( q_{it} = e_{it}L_{it} \), hence \( m_{it} > 0 \) when \( e_{it} < 1 \). Hoarding occurs due to the existence of labor rigidities in the short run (e.g., fire and hire costs); firms adjust the effort of workers and reassign the labor force to non-directly productive activities such as maintenance or training. The response of average labor productivity to demand shocks in this case is:

\[
\frac{d(Y_{it}/L_{it})}{d\epsilon_{it}} = A_{it} \frac{Y_{it}}{L_{it}} \frac{\partial Y_{it}}{\partial A_{it}} \frac{\partial A_{it}}{\partial \epsilon_{it}} > 0
\]

Equation (6) is similar to that of the traditional model, except for the scaling to \( e_{it} \) and the second term. Since the latter is positive, labor productivity could be procyclical if \( m_{it} \) is large enough (or effort \( e_{it} \) is small enough). That is, introducing varying levels of effort, the response of labor productivity to a demand shock could be the opposite of that in the traditional model.

Increasing returns to scale. In the absence of technology shocks and labor hoarding, one should expect that firms vary the effective utilization of inputs proportionally when the production function has increasing returns to scale (Hall, 1990 and Basu, 1996). It can be assumed that the rate of capital utilization displays a linear relationship with labor demand, \( u_{it}K_{it} = \phi L_{it} \). The production function becomes \( Y_{it} = A_{it}F_{it}(\phi L_{it}, L_{it}) \) and the response of labor productivity to a demand shock is procyclical, since:

\[
\frac{d(Y_{it}/L_{it})}{d\eta_{it}} = A_{it} \frac{\partial L_{it}}{\partial \eta_{it}} \left( L_{it} \frac{dF_{it}}{dL_{it}} - F_{it} \right) \frac{\partial \phi}{\partial \eta_{it}} \frac{\partial \phi}{\partial \eta_{it}} > 0
\]

External effects. Following Caballero and Lyons (1992) assume that production takes place in the traditional environment, except for the presence of external effects not associated to input variations. These externalities could emerge from the increased possibilities of matching among agents (and profits) that arise in large-size markets. Since the magnitude of transactions between firms and their
customers is the key factor in the transmission of short-run external effects, these externalities are captured in the production function through a factor that consider the level of aggregate economic activity ($\upsilon > 0$). The effect of economic activity on the fluctuations of average labor productivity is clearly positive:

$$\frac{d\left(\frac{Y_{it}}{L_{it}}\right)}{d\eta_{it}} = A_{it} \frac{\partial Y_{it}}{\partial Y_{it}} L_{it} > 0$$

3. **MODEL ENCOMPASSING**

When confronting these alternative explanations of procyclical labor productivity with the data it is necessary to setup an encompassing model and deal with the existence of intermediate inputs and market power. Fernald and Basu (2000) show that conventional measures of labor productivity (e.g., value added per worker) are sensitive to changes in intermediate goods and, thus, do not provide a reliable basis for assessing its cyclical properties. We start by including intermediate inputs in the production function and, then, decompose gross-output growth in terms of variations in utilization of inputs, imperfect competition, and technical change. Next, we focus on aggregation issues.

**Dealing with intermediate inputs**

As a starting point, consider the following gross-output ($GY$) equation

$$GY_{it} = F\left(\tilde{K}_{it}, \tilde{L}_{it}, M_{it}, T_{it}\right)$$

where $\tilde{K}_{it} = u_{it}K_{it}$ and $\tilde{L}_{it} = e_{it}L_{it}$, $M_{it}$ represents intermediate inputs and $T_{it}$ is a technology index included to capture the correct Solow residual in the empirical estimations.

Let the firm’s production function be locally homogeneous of degree $\gamma$ in total inputs (constant returns implies that $\gamma = 1$). Returns to scale can be written in two equivalent forms. First, as the sum of output elasticities

$$\gamma = \frac{F_{K} \tilde{K}_{it}}{Y_{it}} + \frac{F_{L} \tilde{L}_{it}}{Y_{it}} + \frac{F_{M} M_{it}}{Y_{it}}.$$  

Second, if the firm minimizes costs, the local degree of returns to scale is the inverse of the elasticity of costs with respect to output

$$\gamma_{\left(GY_{it}\right)} = \frac{C_{it}\left(GY_{it}\right)}{GY_{it}MC_{it}\left(GY_{it}\right)} = \frac{AC_{it}\left(GY_{it}\right)}{MC_{it}\left(GY_{it}\right)} = \frac{AC_{it}\left(GY_{it}\right)}{MC_{it}\left(GY_{it}\right)} \text{ where } C_{it} \text{ is the total cost function, } AC_{it} \text{ is the average cost, and } MC_{it} \text{ is the marginal cost. Increasing returns may reflect overhead (fixed) costs or decreasing marginal cost; both imply that average cost exceeds marginal cost. If increasing returns take the form of}$$
overhead costs, then \( \gamma(GY_i) \) is not a constant structural parameter, but depends on the level of output of the firm. As production increases, returns to scale fall as the firm moves down its average cost curve.

Assume that firms charge a price that is a markup over marginal cost \( \mu_i = P_i / MC_i \). The markup is a behavioral parameter while returns to scale are a property of the production function. Nevertheless, they are related:

\[
\gamma_i (GY_i) = \frac{C_i(GY_i)}{GY_iMC_i(GY_i)} = \frac{P_i}{MC_i(GY_i)} = \mu_i (1 - s_i)
\]

where \( s_i \) is the share of pure economic profit in gross revenue. From equation (10) it is clear that if economic profits are small (or zero as in perfect competition) markups tend to be approximately equal to returns to scale.

Taking log differences of equation (9) –which we denote by \( d \)– we can express changes in gross output as:

\[
dGY_i = \frac{F^K_i K_i}{Y_i} dK_i + \frac{F^L_i L_i}{Y_i} dL_i + \frac{F^M_i M_i}{Y_i} dM_i + dt_i
\]

Cost minimization puts additional structure to this equation. If firms take the price of all the inputs as given, the first order conditions for cost minimization are \( P_i F^j_i = \mu_i P^j_i \) where \( j = K, L, \) or \( M \). These conditions allow us to write output elasticities as the product of the markups multiplied by the share of the expenditure on each input divided by gross output:

\[
F^j_i = \frac{P^j_i Y_i}{PG_Y} = s^j_i
\]

The shares \( s^K_i, s^L_i \) and \( s^M_i \) add up to less than one when firms make pure profits. Substituting for output elasticities in equation (11) and making explicit the utilization level of capital and effort by worker we obtain:

\[
dGY_i = \mu_i \left( s^K_i (dK_i + du_i) + s^L_i (dL_i + de_i) + s^M_i dM_i \right) + dt_i
\]

collecting terms

\[
dGY_i = \mu_i \left( s^K_i dK_i + s^L_i dL_i + s^M_i dM_i \right) + \mu_i \left( 1 - s^M_i \right) \left[ \frac{s^K_i du_i + s^L_i de_i}{1 - s^M_i} \right] + dt_i
\]

\[
= \mu_i dx_i + \mu_i \left( 1 - s^M_i \right) dw_i + dt_i
\]
hence, the growth in gross output \( dGY_t \) can be written as a function of a revenue-weighted measure of growth in inputs \( dx_{it} \), a proxy for variations in capital utilization and effort \( dw_{it} \), and a residual that captures technical change \( dt_{it} \).

Since we are interested in average labor productivity defined as value added per worker, it is necessary to adjust equation (14) accordingly. Valued added growth is calculated by subtracting from gross output the contribution of intermediate goods weighed by revenue share. Define the growth rate in a firm’s value added \( dVA_{it} \) as:

\[
dVA_{it} = \frac{dGY_{it} - s_M dM_{it}}{1 - s_M}
\]

consequently,

\[
dVA_{it} = \mu_i \left( \frac{s^K_{it}}{1 - s_M} dK_{it} + \frac{s^L_{it}}{1 - s_M} dL_{it} + dw_{it} \right) + \left( \mu_i - 1 \right) \frac{s^M_{it}}{1 - s_M} dM_{it} + \frac{dt_{it}}{1 - s_M}
\]

Equation (16) implies that valued added growth does not subtract the full productive contribution of intermediate inputs. In the presence of markups the output elasticity of intermediate goods is greater than its revenue share. Changes in output will not lead to proportional changes in the use of intermediate inputs. Therefore, value-added growth does not subtract off the full productive contribution of intermediate inputs. It is possible that value added growth could be a function of primary input growth alone, in the case where intermediate inputs move in tandem with primary inputs (e.g., fixed proportions).

Equation (16) can also be rewritten as:

\[
dVA_{it} = \mu_i \left( \frac{s^K_{it}}{1 - s_M} dK_{it} + \frac{s^L_{it}}{1 - s_M} dL_{it} \right) + \left( \frac{\mu_i}{1 - s_M} - 1 \right) \frac{s^M_{it}}{1 - s_M} \left( dM_{it} - dGY_{it} \right) + \frac{dt_{it}}{1 - s_M}
\]

Again, equation (17) indicates that value added growth is related to growth rates of primary inputs, factor utilization, the share of intermediate goods in output ratio, and technology changes.

Aggregation

Since the empirical analysis is performed at the industry level, aggregation is necessary. Aggregate inputs are defined as the simple sum of industry levels quantities. The aggregate value added growth rate is defined as \( dVA_t = \sum_{i=1}^{N} \theta_i dVA_{it} \), where \( \theta_i \) is the firm’s share of nominal value added in the industry. Fernald and Basu (2000) show that using this definition and equation (17) it is possible to derive the basic aggregation equation:
(18) \[ dVA_t = \bar{\mu}_t^r dx_t^r + du_t + R_t + dt_t^r \]

where \( dx_t^r = s_L^r dL_t + s_K^r dK_t \) is the growth in revenue-share-weighted aggregate primary inputs, \( \bar{\mu}_t^r = \sum_{i=1}^{N} w_i \mu_v^i \) is the average-firm value-added markup, \( du_t = \sum_{i=1}^{N} w_i \mu_v^i du_{it} \) is the average-firm utilization growth (weighted by markups), and \( dt_t^r = \sum_{i=1}^{N} w_i \frac{dt_{it}}{1-\mu_s^i} \) is the is average value-added technology change.

Variable \( R_t \) represents the various outcomes that arise from the reallocation of resources and production within each industry due to the heterogeneity of firms. First, reallocating resources from low- to high-markup firms shifts resources towards uses that are more highly valued by consumers. If the variability of firms’ inputs is correlated with market power, then imperfect competition affects aggregate productivity even if the average markup is small. Second, shifting labor and capital from firms where it has a low shadow value to firms where it has a high shadow value increases aggregate output and average productivity. Third, reallocation of materials reflects the extent to which measured real value added depends on the intensity of intermediate-input use. Firm-level value added is useful for national accounting, regardless of technology or market structure. However, with imperfect competition, value-added growth does not subtract off the full marginal product of intermediate inputs. Growth in primary inputs captures some of this productive contribution, but some “wedge” may remain.

Aggregate labor productivity growth is defined as \( \bar{\zeta}_t = \frac{VA_t}{L_t} \), hence:

\[ \begin{align*}
z_{it} &= dVA_t - dL_t = \bar{\mu}_t^r dx_t^r + du_t + R_t + dt_t^r - dL_t \\
&= \bar{\mu}_t^r dK_t^r + (\bar{\mu}_t^r - 1)dL_t + du_t + R_t + dt_t^r 
\end{align*} \]  

(19)

4. **Evidence on Average Labor Productivity**

The industrial sector in Chile represented around 18\% of GDP in the 1979-2001 period and accounted for nearly 35\% of exports and 15\% of employment (see Table 1). The share of industry in GDP has gradually declined over the years as a result of the expansion of services, yet it remains as an important sector in terms of wealth creation, labor demand, and exports. For the empirical section we split the sample in two sub-periods. The first sub-period, running from 1979 to 1990, is characterized by major structural and sector reforms (including domestic market liberalization, privatization of state-owned firms, and opening the economy to foreign competition) and also by the severe recession of
The second sub-period of 1991-2001 is characterized by macroeconomic stability, vigorous growth, and a marked increase in average productivity levels. While this period is considered to be one of the most successful in Chilean history (dubbed the “golden decade”), the depth and length of the 1998-2001 recession unveiled an important sensitivity of the economy to negative shocks.

These two distinctive periods of Chile’s economic history allow us to study the response of firms and sectors to very different environments. As the economy underwent deep structural transformations in the 1980s and 1990s, relative prices changed dramatically. The relative price between traded and non-traded goods changed as a result of opening to foreign competition; the relative price of factors and intermediate goods changed as a result of market liberalization; and the relative cost of technology changed as firms were granted access to international markets at stable, competitive exchange rates. Consequently, there were significant changes in the incentives faced by firms, leading to substantial adjustments within firms, among firms, and across sectors. In all sectors, firm entry and exit was substantial. Bergoeing and Repetto (2006) estimate entry and exit rates at around 6% per year. The 1991-2001 period, on the other hand, was comparatively more stable, thus allowing firms to engage in longer-horizon investments. The response of industrial firms was not as vigorous as that of GDP, as seen in Table 1, but exports expanded substantially.

Aggregate figures, however, hide a wealth of experiences at the sector and firm level. In order to explore the microeconomic side of economic growth in Chile, we use data from the National Annual Manufacturing Survey (ENIA) produced by the Chilean Bureau of Statistics (INE). The ENIA survey provides information for about 5,000 plants per year, operating with more than ten workers in eighty industries from 1979 to 2001. In this study, the unit of observation for the empirical analysis is a four-digit International Standard Industry Classification (ISIC) code industry.

<table>
<thead>
<tr>
<th>Period</th>
<th>Share of industry (%) in:</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GDP</td>
<td>Employment</td>
<td>Exports</td>
<td></td>
</tr>
<tr>
<td>1979-2001</td>
<td>17.7</td>
<td>15.6</td>
<td>35.9</td>
<td></td>
</tr>
<tr>
<td>1979-1990</td>
<td>19.5</td>
<td>15.4</td>
<td>30.9</td>
<td></td>
</tr>
<tr>
<td>1991-2001</td>
<td>15.8</td>
<td>15.5</td>
<td>41.4</td>
<td></td>
</tr>
</tbody>
</table>

Source: author’s elaboration based on Central Bank of Chile (2005).
The database was initially obtained for the period 1979-1997 and later updated to 2001 using plant-level information and our aggregation methodology. Plant-level data is available for the 1979-2001 period but inconsistencies make it difficult to aggregate the information to obtain robust industry series at the four-digit ISIC level. As a robustness check of our calculation, we matched our aggregation for 1997 to that provided by ENIA. The methodology to deal with data inconsistencies is as follows. First, we removed observations with discontinuity in information across time. Second, we removed observations with no information on value added and employment, those where value added was greater than gross output, and those where value added and/or gross output were negative. As customary in empirical studies of productivity cycles, value added is defined as gross output less the total costs of intermediate goods and services plus the net change in inventories. After these adjustments we were left with a database of eighty sectors (hereafter, the ENIA sample). Although we excluded 21 sectors from the database, we deemed the restricted sample to be representative of manufacturing since the value added of the eighty industries included in the restricted sample represents more than 98% of the total value added of the original database for the whole period. We then computed a measure of total worked days, as the product of two variables reported by ENIA: average total occupation and total working days per year. Then, labor productivity is obtained as the quotient of value added and total days worked.

Table 2 shows the growth of the Chilean economy and industry in the 1979-2001 period. GDP grew on average at around 4.8% while employment expanded at around 2.3%, leading to an average increase in labor productivity of 2.5% per year. Industrial output and labor productivity grew more moderately at around 3% and 1%, respectively. With regards to the sample of firms used in this paper, we present data for the aggregate, average and median firm, the latter to avoid the distorting effect of a few sectors where very large firms operates. It can be seen that the growth rate of value-added in ENIA firms is comparable to that of GDP and much higher than that of the industrial sector as measured by national accounts. Employment in ENIA firms—obtained directly from the surveys—grew much slower than in the rest of the economy or the industrial sector. This explains why average labor productivity in ENIA firms grew much faster than in the rest of the economy. The differences in employment growth between ENIA firms and the rest of the economy lies in that ENIA excludes micro businesses (less than 10 employees) that are typically labor intensive. Finally, it can be seen that among ENIA firms there are differences in long-run dynamics: while in most sectors both output and growth expanded, value added in a few sectors actually contracted. However, even in these latter sectors, labor productivity ought to have expanded on average since only in six of them productivity actually decreased.

---

3Average total occupation is the average of data on employees, workers, and employers per firm surveyed on four occasions in each year (February, May, August, and November). Total working days is the number of days in which each firm was in activity.
A second interesting aspect of ENIA firms is their structural (cross section) and dynamic (time series) heterogeneity in productivity. A few sectors have very high productivity levels that distort to a large extent the average of the manufacturing sector. These are the tobacco, petroleum, copper mining, pulp plants, and paper and printing firms. Figure 1 plots average labor productivity for the ENIA sample and a sub sample excluding the sectors with largest productivity (hereafter called the restricted sample). It can be noted that when excluding those sectors, average industrial productivity is reduced by about 25%. The dispersion of productivity between sectors remains stable throughout the period. Despite the distortion in average productivity levels induced by the most productive sectors, the dynamic (time series) behavior of industrial productivity is largely unaffected, as is apparent in Figure 1. It can be seen that after 1991, productivity recovers its pre-crisis level and starts to increase at a steady pace (around 5% per year), justifying the split of the sample in two sub periods (1979-1990) and (1991-2001) for the empirical analysis.

Figure 2 presents histograms of average labor productivity for the complete and restricted samples. The first graph shows clearly the large differences in productivity between the five most productive sectors and the rest of the industries. On average, these five sectors have productivity levels around ten times higher than the average ENIA industry. Substantial heterogeneity in productivity nevertheless persists in the restricted sample, as indicated in the second histogram.

We also study changes in the distribution of relative productivity using the quintile-based transition matrix. For 1979 and 2001, we compute the quintiles of the distribution of firms in the ENIA sample according to their productivity levels. In the last column of Table 3 it can be seen that there are substantial differences in productivity levels, being sectors in the fifth quintile around ten times more productive than those in the first two quintiles.

<table>
<thead>
<tr>
<th>National Accounts</th>
<th>Sample of ENIA firms</th>
<th>Number of industries with</th>
</tr>
</thead>
<tbody>
<tr>
<td>GDP</td>
<td>Industrial Sector</td>
<td>Aggregate Average Median</td>
</tr>
<tr>
<td>Value Added</td>
<td>4.8 3.0</td>
<td>4.2 3.5</td>
</tr>
<tr>
<td>Employment</td>
<td>2.3 2.0</td>
<td>0.4 0.2</td>
</tr>
<tr>
<td>Productivity</td>
<td>2.5 1.0</td>
<td>3.8 3.3</td>
</tr>
</tbody>
</table>

Source: author’s elaboration based on Central Bank of Chile (2005) and ENIA.
PROCYCLICAL PRODUCTIVITY IN MANUFACTURING

FIGURE 1
AVERAGE LABOR PRODUCTIVITY
ALL ENIA FIRMS IN 1979 = 100

FIGURE 2
HISTOGRAMS OF LABOR PRODUCTIVITY AT THE SECTOR LEVEL,
1979-2001

Also note that sectors have very similar productivity levels in the first three quintiles, suggesting the possibility of significant dynamic adjustments among sectors in terms of productivity. The transition matrix confirms this suspicion. It computes the percentage of sectors that were in one quintile in 1979 and continued to be in such quintile or moved to different quintile in 2001. Note that we use relative productivity. So, if productivity in all sectors increases by say 5%, relative productivity and its distribution by quintiles remain unaffected. The results are presented in Table 3, with quintiles identified from 1 to 5, indicating that, for example, 12.5% of the sectors in the lowest productivity quintile in...
1979 moved to the second quintile by 2001. As expected, sectors in the high productivity tail tend to remain in their origin quintiles. Around 70% of firms in the fifth quintile in 1979 –i.e. where productivity levels are around four times the average productivity in manufacturing– remained in such quintile by 2001. This is reasonable because these sectors are capital intensive, have ample access to financial resources and tend to lead in technology adoption. On the other hand, around half of the sectors at the lower end of productivity levels remain in such quintiles by 2001. It should be noted, however, that there is substantial mobility. Around 60% of the sectors that in 1979 had average productivity levels in the third quintile, changed quintile by 2001. We thus conclude that the dynamics of labor productivity have been important within and among industries in the manufacturing sector.

Finally, we study the cyclical behavior of average labor productivity using the correlation between detrended measures of labor productivity and value added. We detrend both variables using the Hodrick-Prescott (1997) filter. Table 4 presents the correlations for the economy and the industrial sector, for the complete period of analysis and the two sub-periods. For the whole economy there is evidence of procyclicity in labor productivity; correlation is 0.76 for the entire period and 0.90 in the sub period 1991-2001. This fact has been reported in previous studies (e.g., Bergoeing and Soto, 2005). Nevertheless, at the industry level measured by national accounts we found the somewhat surprising result that correlations are negative, although statistically insignificant. The sample of ENIA firms presents also non-significant correlations in both sub-periods, reproducing the results of the industrial sector according to national accounts. This, again, points to the need of studying labor cyclicality at the sector level, which we undertake in the next section.

### Table 3

<table>
<thead>
<tr>
<th>Quintiles in 2001</th>
<th>Relative productivity by quintile in 2001(*)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>56.3 12.5 18.8 12.5 0.0 0.3</td>
</tr>
<tr>
<td>2</td>
<td>31.3 56.3 6.3 6.3 0.0 0.5</td>
</tr>
<tr>
<td>3</td>
<td>0.0 31.3 43.3 18.8 6.3 0.6</td>
</tr>
<tr>
<td>4</td>
<td>12.5 0.0 25.0 37.5 25.0 1.0</td>
</tr>
<tr>
<td>5</td>
<td>0.0 0.0 6.3 25.0 68.8 4.0</td>
</tr>
</tbody>
</table>

Source: author’s elaboration based on ENIA.
Note: (*) Computed as average productivity by quintile as fraction of total manufacturing average productivity.

The HP filter presents some limitations (King and Rebelo, 1993; Harvey and Jaeger, 1993). In a previous version of this paper we used three detrending methods: linear trends, the HP filter, and a heuristic filter proposed by Rotemberg (1999). Since the main conclusions were insensitive to the detrending method, we report only the HP filtered results.
This evidence is clear on two accounts. First, aggregate figures may distort our understanding of the dynamics of labor productivity as they smooth out important changes in productivity levels experienced by the different sectors. Second, aggregate figures may be distorted by a few very large sectors in which labor productivity is markedly higher than in the rest of the sample. Both elements suggest the importance of exploring the link between labor productivity and economic fluctuations at the sector—instead of the aggregate—level.

5. **Aggregation Bias**

In this section we document the aggregation biases arising in the construction of the aggregate productivity series and their distorting effect on the cross-industry correlation between cycles in labor productivity and economic activity. To obtain cycles, we detrend the series for each industry using the Hodrick-Prescott filter and then compute the cyclical correlations between value added and labor productivity.

5.1. **Value Added-Labor Productivity Cyclical Correlations**

Consistently with our results using national accounts data, the cyclical correlation between manufacturing labor productivity and value added using the full ENIA sample is not statistically different from zero.\(^5\) This result contrasts significantly with the average of the cyclical correlations across industries that is positive and greater than 0.6. Consequently, the average correlation differs significantly from the correlation of aggregates. This result is unexpected considering the strong evidence of procyclicality found at the industry level in

\(^5\) This is considering the 95% confidence level. Standard error bounds computed as \(\pm 2/\sqrt{T}\).
the literature across countries (e.g., Inklaar, 2005; Jimenez and Marchetti, 2002). Hart and Malley (1999) is the only study we are aware of which finds a result similar to ours. However, they do not give much attention to this dichotomy nor attempts to explain its nature.

In Figure 3 we ordered the industries according to their ISIC codes (Revision 2) and we plotted the individual productivity-value added correlations (dots) together with the cumulative productivity-value added correlations (solid line). The cumulative correlations were obtained as the productivity-value added correlations of successive aggregations of industries. Hence, the first point to the left in the cumulative correlation line is the cyclical correlation for the first industry according to the ISIC four-digit code, while the last point to the right corresponds to the cross-industry aggregate correlation. Note how the cross-industry aggregate figure is distorted by the biggest industry (sector 3721 of non-ferrous metal industries), which accounts for 14% of the sample value added.

Indeed, if we exclude the ISIC category 3721, the cumulative correlation displays a smoother pattern and it is constant around 0.05 when we successively aggregate the last 50% of the industries ordered according to their ISIC codes. The cumulative correlation is decreasing when we aggregate industries with ISIC codes between 31xx and 35xx (mainly food, beverages, tobacco), and then it fluctuates around 0.05 when we incorporate industries with ISIC codes between 35xx and 39xx (i.e., from chemicals to machinery).
There is a clear pattern of industry clustering related to their ISIC codes. Evidence of clustering in the ISIC space is not novel for other countries but it has never been reported for Chile.\footnote{Using census data for the US, Bernard \textit{et al.} (2005) find evidence of complementarity in demand or supply among close industries in the US Standard Industry Classification (SIC) space.} In the figure we also graphed the 95\% confidence level significance bounds, indicating that sectoral correlations within these bounds are not statistically different from zero. Considering this, we can see that aggregate productivity is a-cyclical regardless of the final aggregation of industries and it is mainly procyclical at the industry level, as most of the industries present a positive and statistically significant productivity-value added correlation.

Returning to our general result, the question is why does the aggregate correlation differ so much from the average one. In the next subsection we present a decomposition of the aggregate correlation that aims to explain this apparently contradictory result.

5.2. Aggregate Correlation Decomposition and Aggregation Bias

In this subsection we describe in detail our calculations of cyclical correlations and identify the aggregation bias. Let \( \bar{v}_i^t = v_i^t - \bar{v}_i \) be the cyclical value added for industry \( i \) in time \( t \), defined as the difference between actual value added and its trend \( \bar{v}_i \). Accordingly, \( \bar{z}_i^t = z_i^t - \bar{z}_i \) is the detrended labor productivity in industry \( i \). For convenience, we compute the trend of the level of the variables and not of their logs.\footnote{Working with logs or levels does not change the qualitative results on the distribution and aggregates of cyclical correlation.} This allows us to define:

\[
\bar{v}_i = \sum_{i=1}^{N} \bar{v}_i^t
\]

\[
\bar{z}_i = \frac{\sum_{i=1}^{N} v_i^t}{\sum_{i=1}^{N} l_i} - \frac{\sum_{i=1}^{N} v_i^t}{\sum_{i=1}^{N} l_i} = \sum_{i=1}^{N} \bar{z}_i^t l_i - \sum_{i=1}^{N} \bar{z}_i^t l_i = \sum_{i=1}^{N} \bar{z}_i^t
\]

where \( N \) is the number of industries, and \( \bar{z}_i \) is a detrended weighted labor productivity \( i \). Note that \( \frac{\bar{z}_i l_i}{l_i} \) measures the contribution of labor productivity in sector \( i \) to total labor productivity in an industry, weighted by its labor share. Following Navarro (2005) The aggregate cyclical correlation between value added and labor productivity is defined as:
where $\sigma(\bar{v}_i, \bar{z}_j)$ is the covariance between value added and labor productivity and $\sigma(\bar{v}_i)$ and $\sigma(\bar{z}_j)$ are the standard deviations of each variable. Now consider the definition of the covariance term and use equation (20) to obtain:

$$\sigma(\bar{v}_i, \bar{z}_j) = \sum_{i=1}^{N} \sigma(\bar{v}_i, \bar{z}_j) + \sum_{i \neq j} \sum_{i=1}^{N} \sigma(\bar{v}_i, \bar{z}_j)$$

or equivalently,

$$\rho_{\bar{v}_i, \bar{z}_j} = \frac{\sum_{i=1}^{N} \sigma(\bar{v}_i, \bar{z}_j) \sigma(\bar{z}_j)}{\sigma(\bar{v}_i) \sigma(\bar{z}_j)} + \sum_{i \neq j} \sum_{i=1}^{N} \rho_{\bar{v}_i, \bar{z}_j} \frac{\sigma(\bar{v}_i) \sigma(\bar{z}_j)}{\sigma(\bar{v}_i) \sigma(\bar{z}_j)}$$

The correlation between detrended aggregate value added and detrended labor productivity is explained by the aggregation of the sector specific correlations between value added and weighted labor productivity and by the aggregation of the cross correlations between value added in sector $i$ and weighted productivity in sector $j$. Although $\rho_{\bar{v}_i, \bar{z}_j}$ does not measure exactly the individual correlations ($\rho_{\bar{v}_i, \bar{z}_j}$) reported in this paper, we could write equation (23) as follows (details are given in the Appendix):

$$\rho_{\bar{v}_i, \bar{z}_j} = \sum_{i=1}^{N} \rho_{\bar{v}_i, \bar{z}_j} \frac{\sigma(\bar{v}_i) \sigma(\bar{z}_j)}{\sigma(\bar{v}_i) \sigma(\bar{z}_j)} + \sum_{i \neq j} \sum_{i=1}^{N} \rho_{\bar{v}_i, \bar{z}_j} \frac{\sigma(\bar{v}_i) \sigma(\bar{z}_j)}{\sigma(\bar{v}_i) \sigma(\bar{z}_j)}$$

where $\bar{z}_{it} = \sum_{i=1}^{N} \bar{z}_i \left(1 - \frac{L_i}{L_t}\right) - \sum_{i=1}^{N} \bar{z}_i \left(1 - \frac{L_i}{L_t}\right)$. It becomes clear, then, that the first term of equation (23) is increasing in $\rho_{\bar{v}_i, \bar{z}_j}$, the size of the industry in terms of its contribution to total employment, and the relative volatility of the industry value added and productivity $\rho_{\bar{v}_i, \bar{z}_j}$. Note also that according to the second term of equation (23) $\rho_{\bar{v}_i, \bar{z}_j}$ is also increasing in the co-movements between the industries, approximated by $\rho_{\bar{v}_i, \bar{z}_j}$. 
5.3. Interpretation of Results

To illustrate how equation (23) works to explain our results consider the aggregate correlation for the sample of 79 industries (excluding sector 3721), $\rho(\tilde{v}_a, \tilde{z}) = 0.06$. In addition, note that, in apparent contradiction, $\sum_{i=1}^{N} \rho(\tilde{v}_i, \tilde{z}_i) / N = 0.64$. When computing the decomposition of $\rho(\tilde{v}_a, \tilde{z})$ given by equation (22) we obtained that the first term of the right hand side is equal to 0.30 while the second term is –0.24. Finding that the first term is positive is not surprising because in most of the industries $\rho(\tilde{v}_a, \tilde{z}_i)$ is positive. It follows, then, that the reason for the coexistence of aggregate a-cyclical productivity and average procyclical productivity is the presence of aggregate negative cross-correlations between value added and productivity cycle among industries. This indicator of negative co-movement across industries is summarized by the value of –0.24 that we obtained for the second term of the right hand side of equation (22).

This explains why the cumulative correlation line in Figure 3 is decreasing as we aggregate industries. When we add industry $i$ to the sample and calculate $\rho(\tilde{v}_a, \tilde{z})$ what matters is not only the value of $\rho(\tilde{v}_a, \tilde{z}_i)$ in that particular industry, but also how its productivity and value added is related with the value added and productivity in all other industries. If an increase in productivity in industry $i$ has a positive effect on value added in the rest of the industries and/or if an increase in productivity of the rest of the industries has a positive effect on the value added of industry $i$, we should expect $\rho(\tilde{v}_a, \tilde{z})$ to increase when such industry is added to the sample.

What actually happens in the Chilean data is exactly the opposite. That is, according to our results, productivity and value added cycles at the aggregate level seem to be negatively correlated across industries in Chilean manufacturing. To illustrate this point, in Figure 4 we show the decomposition of $\rho(\tilde{v}_a, \tilde{z})$ based on equation (23). For every industry, we graph $\sigma(\tilde{v}_i, \tilde{z}_i)$ and $\sigma(\tilde{v}_i, \tilde{z}_i) + \sum_{j \neq i}^{N} \sigma(\tilde{v}_j, \tilde{z}_j)$ relative to $\sigma(\tilde{v}_a, \tilde{z})$. This presentation of the covariance data allows us to identify the contribution of every industry to the aggregate covariance. Note that $\sigma(\tilde{v}_i, \tilde{z}_i)$ is the covariance between value added and weighted productivity in industry $i$ and $\sum_{j \neq i}^{N} \sigma(\tilde{v}_j, \tilde{z}_j)$ is the sum of the covariances between productivity in industry $j$ and value added in the other industries. If, consistently with the evidence of the literature, labor productivity leads the cycle we can interpret $\sum_{j \neq i}^{N} \sigma(\tilde{v}_j, \tilde{z}_j)$ as the effect of productivity shocks in sector $j$ on the value added of the other industries.

Note that $\sigma(\tilde{v}_a, \tilde{z}_i)$ is positive for all industries. However, if we consider $\sigma(\tilde{v}_a, \tilde{z}_i) + \sum_{j \neq i}^{N} \sigma(\tilde{v}_j, \tilde{z}_j)$ we see that the addition of some industries to the sample increases $\sigma(\tilde{v}_a, \tilde{z})$ while the addition of some others decreases it. The most
prominent example is that of Petroleum Refineries (sector 3530). Although productivity is highly procyclical in this industry, its cycle is negatively correlated to the value added of the other 78 industries in the sample. Then, including this industry in the sample reduces the aggregate productivity-value added correlation. Since this industry contributes to more than 6% of the total value added in the sample, the effect of adding this industry to the sample is large. A similar pattern is observed for Pulp and Paper industries (sector 3411), which produces about 5% of the total value added. Again, this industry displays procyclical productivity but its productivity cycle is negatively correlated to the value added of the other industries, even though the net effect of including sector 3411 on $\sigma_{va,z}/\sigma_{va}$ is positive.

In general, we observe a negative association between $\sigma_{va,z} + \sum_{j \neq i} \sigma_{vai, zj}$ and the share of each sector in total value added. Indeed, the correlation is –0.23 and significant at 5% confidence level. The largest industries distort the aggregate $\sigma(\tilde{v}_i, \tilde{z}_i)$ not because they do not show procyclical productivity but because their productivity cycles are negatively correlated to the activity of the majority of the other industries in the sample. This group of industries generating cross countercyclical behavior represents 62% of total value added.

To summarize, our results provide evidence of significant heterogeneity not only in the structure but also in the cycles of the different industries. Productivity is procyclical across industries but the cyclical phases of the industries are significantly different between each other, leading to an aggregate a-cyclical productivity. In particular, this behavior could be explained in view of the high
concentration of Chilean manufacturing. Although the biggest industries display procyclical productivity, the cycles of these industries are not related or they are negatively related to the ones of the other industries in ENIA. This is one of the main results of our paper.

At this point it seems natural to ask what determines the cyclicality of productivity. Our previous discussion proved useful to clarify that productivity is procyclical in most of the industries in Chilean manufacturing. That allows us to narrow down our question and instead analyze the determinants of procyclical productivity in Chilean manufacturing. This is what we do in the next section.

6. Testing Alternative Theories of Procyclical Labor Productivity

In this section we test the specification in section 4 using data for 58 of the original eighty sectors contained in the ENIA sample. Data limitations preclude us from using the full sample. First, we excluded several “residual” industries, i.e. those labeled by the INE as “not elsewhere classified”, since data were unwarranted. Second, 26 industries were dropped from the database because irregularities in the data on costs made estimations unreliable. Nevertheless, the industries considered in the econometric testing represent on average 86% of the industry gross output in the 1979-2001 period.

Shares of the different inputs were obtained as the average use of inputs in the whole period of analysis. To compute the share of capital in each sector it was necessary to compute a series of the required payments for unit of capital and estimate the user cost for each unit of capital. An adequate measure of cost of capital in each sector was unavailable; consequently as a proxy we used the sum of the average real lending interest rate of the financial system plus a depreciation rate of 10%, as suggested by Bustos et al. (2000). Using lending rates is supported by the fact that most financing of firms in Chile are loans from the banking sector, given that the equity market is shallow.

Estimation of equation (19) would require an index of capital utilization. Abbott et al. (1998) suggest to use as a proxy the growth rate in hours worked. We therefore estimate:

\[ dy_i = c_i + \mu_i dx_i + \alpha_i dh_i + dt_i \]

where \( dh \) is the growth rate in hours worked. Although ENIA data do not include hours worked, additional data on hours worked from the employment surveys of the INE were used to correct the measure of labor input. This equation allows us to compute an appropriate measure of technical change, \( dt_i \), as a residual.

8We excluded sectors such as canning of seafood, some textiles, furs, non-metal furniture, chemicals, pottery and china, manufacture of tools, and shipbuilding.
Equation (25) can be estimated for each industry. As noted by Fernald and Basu (2000), although one could estimate these equations separately for each industry, some parameters (particularly the utilization proxies) are then estimated rather imprecisely. To control for this problem, the 59 sectors were combined into four groups and the constant and the utilization proxy were restricted to be equal across groups. Each system was estimated using three-stage least squares using instrumental variables to avoid correlation between technology shocks and inputs across sectors. The instruments include all lagged independent variables, the rate of growth in the real price of oil (deflated by CPI), the rate of growth in real government spending, and the rate of growth in the real effective exchange rate. Table 5 presents a summary of the econometric results.

### TABLE 5
ECONOMETRIC RESULTS

<table>
<thead>
<tr>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
<th>Group 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>0.016 *</td>
<td>$c$</td>
<td>0.008</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.028</td>
<td>$\alpha$</td>
<td>0.223 *</td>
</tr>
<tr>
<td>$\mu_{3111}$</td>
<td>1.072 *</td>
<td>$\mu_{3211}$</td>
<td>1.358 *</td>
</tr>
<tr>
<td>$\mu_{3112}$</td>
<td>0.863 *</td>
<td>$\mu_{3213}$</td>
<td>0.724 *</td>
</tr>
<tr>
<td>$\mu_{3113}$</td>
<td>1.535 *</td>
<td>$\mu_{3214}$</td>
<td>1.598 *</td>
</tr>
<tr>
<td>$\mu_{3115}$</td>
<td>0.846 *</td>
<td>$\mu_{3215}$</td>
<td>1.197 *</td>
</tr>
<tr>
<td>$\mu_{3116}$</td>
<td>0.586 *</td>
<td>$\mu_{3220}$</td>
<td>1.340 *</td>
</tr>
<tr>
<td>$\mu_{3117}$</td>
<td>1.014 *</td>
<td>$\mu_{3231}$</td>
<td>–0.244</td>
</tr>
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<td>$\mu_{3118}$</td>
<td>0.864 *</td>
<td>$\mu_{3233}$</td>
<td>1.014 *</td>
</tr>
<tr>
<td>$\mu_{3119}$</td>
<td>1.325</td>
<td>$\mu_{3240}$</td>
<td>1.423 *</td>
</tr>
<tr>
<td>$\mu_{3121}$</td>
<td>0.762</td>
<td>$\mu_{3311}$</td>
<td>1.852 *</td>
</tr>
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<td>$\mu_{3122}$</td>
<td>1.022 *</td>
<td>$\mu_{3312}$</td>
<td>1.364 *</td>
</tr>
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<td>$\mu_{3131}$</td>
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<td>$\mu_{3319}$</td>
<td>0.721 *</td>
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<td>$\mu_{3411}$</td>
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<td>$\mu_{3140}$</td>
<td>2.342 *</td>
<td>$\mu_{3909}$</td>
<td>1.835 *</td>
</tr>
</tbody>
</table>

Note (*) significant at 95% confidence.
Source: author’s calculation.

9The groups were formed according to their 2-digit level ISIC classification. Consequently we formed groups for categories 31 (15 industries), 32 to 34 (14 industries), 35 to 37 (13 industries), and 38 to 39 (17 industries).
After estimating equation (25) we calculated the sum of the group-specific constant and the residual of each equation as the measure of technical change in the gross-output production function. These results were inserted in the aggregation equation (19) to decompose aggregate productivity into a technological component plus various non-technological components, including the effects of markups and reallocation of inputs.

The results for the 1979-2001 period and the two sub-periods are presented in Table 6. These results suggest that technical change is the main explanation of the dynamics of productivity in the Chilean industry in the two periods of analysis; one half of total productivity gains are due to improved technologies. However there are marked differences between the two sub-periods. For the 1979-1990 period, technical change is slightly negative, while for the 1991-2001 it accounts for over 80% of productivity growth. These results match closely those by Bergoeing and Repetto (2006) using a similar database but a very different estimation procedure, in particular the slightly negative contribution of TFP in the 1980s.

Using standard sources of growth analysis, Fuentes et al. (2006) also assign to TFP a significant contribution to GDP growth in the 1990-2005 period (around 60%).

<table>
<thead>
<tr>
<th></th>
<th>Change in observed productivity</th>
<th>Change in markups</th>
<th>Change in labor and capital utilization</th>
<th>Technical change</th>
<th>Reallocation of inputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>1979-2001</td>
<td>0.09</td>
<td>0.01</td>
<td>0.00</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>0.23</td>
<td>0.07</td>
<td>0.14</td>
<td>0.25</td>
<td>0.10</td>
</tr>
<tr>
<td>1979-1990</td>
<td>0.04</td>
<td>0.03</td>
<td>0.04</td>
<td>–0.02</td>
<td>0.00</td>
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<tr>
<td></td>
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<td>0.06</td>
<td>0.09</td>
<td>0.28</td>
<td>0.09</td>
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<tr>
<td>1991-2001</td>
<td>0.14</td>
<td>0.00</td>
<td>–0.03</td>
<td>0.12</td>
<td>0.04</td>
</tr>
<tr>
<td></td>
<td>0.23</td>
<td>0.07</td>
<td>0.18</td>
<td>0.19</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Source: author’s calculation.
Reallocation of resources among sectors appears to have been significant only during the 1990s. Again this result is similar to that found by Bergegioing and Repetto, although their point estimate of the contribution of relocation to productivity is markedly higher. Their result however is largely driven by intra industry relocation, whilst ours refers to inter sector relocations. Variations in input utilization were insignificant in the long run, reflecting the fact that we are reporting long-period averages that tend to net out intraperiod variations. Nevertheless, differences become apparent when comparing sub-periods: in the early 1979-1990 period increased utilization of labor and capital plays a significant contribution to productivity growth, while in the 1991-2001 period there is a negative contribution reflecting, most likely, the impact of the reduction in the number of hours worked.

7. Conclusions

This paper studies the dynamics of labor productivity during economic cycles in Chilean in the 1979-2001 period. We use data from the Chilean manufacturing sector to study the cyclical behavior of labor productivity at the industry level, its determinants, and its relationship with economic activity. The paper presents evidence of procyclical labor productivity at the macroeconomic level. However, we find no evidence of correlation between labor productivity and economic activity when using the aggregate data of manufacturing sectors. In addition, when undertaking the analysis sector by sector we found that most industries exhibit significant procyclical productivity. We provide an analytical and empirical explanation for these apparently conflicting results. We document that aggregation biases arising in the construction of the aggregate productivity series distort the cross-industry correlation between cycles in labor productivity and economic activity. This reflects both the substantial heterogeneity of ENIA firms and the distorting effect of the timing of cycles in the different industries. Productivity is procyclical across industries but the cyclical phases of the industries are significantly different between each other, leading to an aggregate a-cyclical productivity.

We also test the determinants of productivity in the Chilean industry using an econometric model that allows us to quantify the relative contribution of technology shocks, changes in markups, variations in the utilization rates, and reallocation of resources among from less to more productive sectors. We found that for the 1979-2001 technical change is the main explanation of the dynamics of productivity. Nevertheless, this contribution is not smooth in time. In the 1979-1990 period, technical change does not contribute to productivity growth, while for the 1991-2001 it accounts for over 80% of productivity growth. With regards to the other determinants of productivity changes, reallocation of resources from less to more productive industries appears to have been significant only
during the 1990s while changes in input utilization were significant mostly in the 1979-1990 period.

REFERENCES


Let \( \sigma(\tilde{v}_i, \hat{z}_i) = \frac{T}{1} \left( \sum_{t=1}^{T} (\tilde{v}_i - \bar{v}_i)(\hat{z}_i - \bar{z}_i) \right) / (T-1) \) be the covariance between value-added and labor productivity. A dot on a variable indicates average over time. Let \( \sigma(\tilde{v}_i, \hat{z}_i) = \sqrt{\frac{T}{\sum_{t=1}^{T} (\tilde{v}_i - \bar{v}_i)^2}} \) and \( \sigma(\hat{z}_i) = \sqrt{\frac{T}{\sum_{t=1}^{T} (\hat{z}_i - \bar{z}_i)^2}} \) the corresponding standard deviations. Then, the covariance can be written as:

\[
(A1) \quad \sigma(\tilde{v}_i, \hat{z}_i) = \frac{T}{1} \left( \sum_{t=1}^{T} (\tilde{v}_i - \bar{v}_i)(\hat{z}_i - \bar{z}_i) \right) / (T-1) = \sum_{t=1}^{T} \left( \frac{1}{N} \sum_{i=1}^{N} \tilde{v}_i - \frac{1}{N} \sum_{i=1}^{N} \hat{z}_i \right) / (T-1)
\]

Consider the second term in parenthesis in equation (A1) and subtract \( \sum_{i=1}^{N} \bar{z}_i \). Then we can rewrite \( \sigma(va, z) \) as

\[
(A2) \quad \sigma(va, z) = \sum_{i=1}^{N} \left( \frac{1}{N} \sum_{i=1}^{N} \tilde{v}_i - \frac{1}{N} \sum_{i=1}^{N} \hat{z}_i \right) / (T-1)
\]

then

\[
(A3) \quad \sigma(va, z) = \sum_{i=1}^{N} \left( \frac{1}{N} \sum_{i=1}^{N} \bar{v}_i - \frac{1}{N} \sum_{i=1}^{N} \bar{z}_i \right) / (T-1)
\]

where

\[
(A4) \quad \bar{z}_i = \sum_{i=1}^{N} \frac{1}{L_i} \left( 1 - \frac{L_i}{L_j} \right) \sum_{j=1}^{N} \frac{1}{L_j} \left( 1 - \frac{L_j}{L_i} \right)
\]

replacing by their corresponding definitions,

\[
(A5) \quad \sigma(va, z) = \sum_{i=1}^{N} \sigma(va, z_i) + \sum_{i=1}^{N} \sigma(va, z_i) + \sum_{i=1}^{N} \sigma(va, z_i) / (T-1)
\]

\[
(A6) \quad \sigma(va, z) = \sum_{i=1}^{N} \left( \frac{1}{N} \sum_{i=1}^{N} \tilde{v}_i - \frac{1}{N} \sum_{i=1}^{N} \hat{z}_i \right) / (T-1)
\]

where \( \sigma(va, z_j) \) is the covariance between the cyclical value added of sector \( i \) and cyclical productivity of sector \( j \). Accordingly \( \sigma(va, z) \) denotes the cyclical covariance between sector \( i \) value added and the productivity measure \( \hat{z}_i \).
The relevance of the expression (A6) is that it allows relating the aggregate covariance with the individual ones. Note that the first two terms of (A6) consider the contribution of the individual covariances to the aggregate. The two other terms control for the cross covariances between valued added in sector $i$ and productivity in sector $j$. In a way, these last two terms are related to the co-movement between the sectors. Equivalently, we can write (A6) in terms of correlations,

$$
\rho_{mz} = \sum_{i=1}^{N} \rho_{mz} \frac{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)}{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)} - \sum_{i=1}^{N} \rho_{mz} \frac{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)}{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)} + \sum_{i \neq j}^{N} \frac{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)}{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)} - \sum_{i \neq j}^{N} \frac{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)}{\sigma(\tilde{\nu}_i)\sigma(\tilde{\zeta}_i)},
$$

which is expression (24) in the main text.