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PROCYCLICAL PRODUCTIVITY: EVIDENCE FROM AN EMERGING ECONOMY

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Resumen

La productividad de los factores tiende a aumentar en booms y caer en recesiones. Este fenómeno no puede ser explicado por las teorías macroeconómicas clásicas, éstas predicen que los cambios en productividad deben ser contracíclicos como resultado de la ley de rendimientos decrecientes al factor. Teorías alternativas explican la prociclicidad como resultado de shocks tecnológicos exógenos, retornos crecientes de escala, errores de medición debido al uso variable de insumos, y economías externas. Sorprendentemente, la productividad observada en el sector industrial chileno es contracíclica. Este trabajo tiene dos objetivos. Primero, estudiamos el comportamiento cíclico de la productividad en 84 sectores de la industria chilena entre 1979 y 1997. Se obtiene que, al contrario de los resultados agregados, los datos sector por sector demuestran que la productividad es inambiguamente procíclica. La principal razón de esta diferencia son las distorsiones del proceso de agregación inducidas por la heterogeneidad en el comportamiento de los sectores. Segundo, estudiamos los determinantes de la productividad usando un modelo econométrico que permite cuantificar la contribución relativa de las cuatro teorías alternativas que explican la prociclicidad. Los resultados indican que 50% de los ciclos de productividad entre 1979 y 1997 se deben a shocks tecnológicos, lo que apoya la hipótesis que los shocks de oferta son la principal fuente del ciclo económico en Chile. El restante 50% de los ciclos proviene principalmente de la reasignación de recursos entre sectores con distinta productividad y, recientemente, por el aprovechamiento de economías de escala. Variaciones en el uso de insumos resultan poco significativas.

Abstract

Average productivity tends to rise during booms and fall during recessions. This fact is at odds with classical macroeconomic theories which suggest that labor productivity should be countercyclical due to the law of diminishing returns to factors. Theoretical explanations for this puzzle include exogenous changes in production technology, increasing returns to scale, measurement errors due to unobserved input variations, external economies and composition effects at the aggregate level. Surprisingly, aggregate data for the Chilean industry show that productivity is countercyclical. This paper has two objectives. First, we study the cyclical behavior of productivity in 84 sectors of the Chilean industry in the 1979-1997 period. We find that, contrary to the results obtained using aggregate indexes, disaggregated data confirm that on average productivity is unambiguously procyclical. The main reason for this difference is that aggregate data provides a distorted assessment of the cyclical component of productivity due to the marked heterogeneity of behavior between sectors. Second, we examine the determinants of productivity in the Chilean industry using an econometric model that allow us to quantify the relative contribution of the four different explanations of procyclical productivity. The results indicate that technology shocks account for 50% of productivity cycles in the 1979-1997 period, thus supporting the supply shocks hypothesis as the main source of business cycles in Chile. The other 50% of the productivity shocks is explained by important reallocation effects among sectors of different productivity and, more recently, by the presence of increasing returns. Variations in the utilization of capital and labor effort were insignificant.

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1. Introduction

Average productivity tends to rise during booms and fall during recessions. This simple fact is at odds with standard macroeconomic theories which suggest that labor productivity should be countercyclical as a direct result of the law of diminishing returns to factors. Consequently, several theories had been advanced to account for the observed procyclical behavior of productivity. The most popular alternative explanations 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, Eichenbaum, and Rebelo, 1993).

One important limitation of this literature is its reliance on aggregate data, either at national level or industry-wide level. While using these type of data is a useful initial step for the analysis, it is limited by numerous aggregation issues that arise in the construction of aggregate figures of productivity, capacity utilization, and resource relocation. This would suggest the use of disaggregated data. A second limitation is that most of the evidence is available for developed economies only.[1] Data from developing economies – which remains largely unexplored– could provide important insights to understand the response of firms to recurrent shocks, given that economic cycles tend to be more pronounced in emerging economies.

In this paper we use data of Chilean industry for the 1979-1997 period, disaggregated at 4-digit levels of the ISIC. The case of Chile is interesting for several reasons. The economy is very dynamic, small for international standards but quite open to foreign markets, and largely free of preferential treatments for selected industries. Chilean firms have grown at impressive rates in the last two decades (real value added grew at over 5% per year) but, at the same time, they have faced important fluctuations in economic activity. Studies using macroeconomic data suggest that, to a large extent, these impressive growth rates are the result of technological renovation and a dramatic change in capital-labor ratios (Bergoeing et al., 2002). Other studies suggest that market deregulation and liberalization has also led to the expansion of dynamic sectors (Lefort, 1997). Cahmi et al. (1997) provide evidence that productivity has increased as a result of entry-exit processes,

[1] See Bernanke and Parkinson (1991) and Fernald and Basu (1999) for evidence on the US economy.

in which new firms are more efficient the incumbents. Consequently, the Chilean experience provides a wealth of information to test these hypotheses.

We provide an initial exploration of the cyclical behavior of labor productivity at the sector level, its determinants, and its relationship with economic activity. A simple model is developed in section 2 to provide a framework for the analysis, embedding the hypotheses described above. Section 3 presents the data and collects aggregate level evidence of procyclical behavior in labor productivity. The main result is that average labor productivity obtained from aggregate industry indexes display a puzzling countercyclical behavior. Section 4 provides evidence that aggregate measures are inadequate as they mask the heterogeneity in the behavior of the different sectors of the economy. Likewise, there exists important time-series heterogeneity which suggest the inadequacy of using decade averages of growth rates when assessing the relative contribution of inputs and productivity. In particular, we found mixed evidence of procyclical and countercyclical productivity at the sectoral level. Section 5 tests the determinants of productivity in the Chilean industry using an econometric model that allows us to quantify the relative contribution of the four abovementioned explanations of procyclical productivity. The results indicate that technology shocks account for 50% of productivity cycles in the 1979-1997 period, thus supporting the supply shocks hypothesis as the main source of business cycles in Chile. The other 50% of the productivity dynamics is explained by important reallocation effects between sectors of different productivity and, more recently, by the presence of increasing returns. Variations in the utilization rates of inputs were not significant. Section 6 collects the main conclusions.

2. A simple analytical framework

The starting point of the analysis is the following generalized production function:

$$Y_{it} = A_{it} F(u_{it} K_{it}, e_{it} L_{it}) Y_t^n \qquad \textbf{(1)}$$

where Y_{it} is the real output of the firm, A_{it} is the 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_t is the aggregate output of the industry. Parameters u_{it} and e_{it} are in the [0,1] interval, while $\nu \geq 0$.[2]

Following Baily, Bartelsman, and Haltiwanger (1996), we assume that each firm faces a demand curve with constant price-elasticity. The inverse demand curve is:

$$P_{it} = D_{it}\, \eta_{it}\, Y_{it}^{-\mu} \tag{2}$$

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, η_{it} is a stochastic i.i.d. shock that affects all firms, and μ is a constant that allows for either competitive (μ = 1) or imperfectly competitive behavior (μ < 1).

Technology evolves according to the following law of motion:

$$A_{it} = (1-\rho)\, A_0 + \rho\, A_{it-1} + \varepsilon_{it} \tag{3}$$

where ε_{it} is a stochastic i.i.d. technology shock and ρ is a constant with values between 0 and 1.

The procyclical behavior of productivity is usually assessed using the correlation between cyclical measures of output (x_t) and labor productivity (x_t). When the correlation $corr(x_t\ ,y_t)>0$, labor productivity is procyclical. On the contrary, when $corr(x_t,y_t)<0$, productivity is countercyclical.

In this simple model, cyclical fluctuations in labor productivity arise in response to economic fluctuations, i.e., as a result of supply and demand shocks. Consequently, we study the sign of $d(Y_{it}/L_{it})/dz_{it}$ (where z_{it} is either a supply or a demand shock) and its effects on $corr(x_t,y_t)$ under alternative assumptions about the structure of the economy (equations 1 to 3). There are five cases of interest.

In the first case, we consider that there are no external effects, unused capital, or idle labor in the firm. Hence, ν=0, u_{it}=1, and e_{it} = 1. Assume also that technology is stationary, i.e., ε_{it}=0. The production function becomes $Y_{it} = A_i\ F(K_{it}\ ,L_{it})$. Cycles are generated by demand shocks (η_{it}) and the response of productivity is:

[2] To simplify the exposition we neglect intermediate inputs. In the empirical section, however, we take these into account.

$$\frac{d(Y_{it}/L_{it})}{d\,\eta_{it}} = \frac{\partial L_{it}}{\partial \eta_{it}} \left(\frac{L_{it} F^{l}_{it} - F_{it}}{L^{2}_{it}} \right) \leq 0 \qquad \textbf{(4)}$$

which is usually negative because the first expression in the right hand side of the equation is positive and the second is negative (F^{l}_{it} is marginal product of labor and, hence, $L_{it}F^{l}_{it}$ is the equilibrium payment to labor).[3] Under these assumptions, which corresponds to the Keynesian or traditional model, average labor productivity is countercyclical. The intuition is that in this model firms do not change their production technology and, therefore, in the short run demand shocks induce a movement along the (decreasing) marginal productivity curve. In general, the empirical evidence on the dynamics of labor productivity does not provide support for this theory (see Barro and King, 1984). If this were the model governing the economy, procyclical productivity would be puzzling because it contradicts the law of diminishing returns.

The second case we consider does not impose particular assumptions with respect to the value of the parameters in the production function, but focuses on technology shocks (ε_{it}) as the driving force of economic cycles. In such case, average labor productivity becomes procyclical since:

$$\frac{d(Y_{it}/L_{it})}{d\,\varepsilon_{it}} = \frac{\partial Y_{it}}{\partial A_{it}} \frac{\partial A_{it}}{\partial \varepsilon_{it}} \frac{Y_{it}}{L_{it}} > 0 \qquad \textbf{(5)}$$

The presence of supply shocks as the main source of economic fluctuations is the standard explanation proposed in the real business cycles literature pioneered by Kydland and Prescott (1982). As described in Cooley (1998), these models are capable of replicating a substantial fraction of the fluctuations in macroeconomic variables, including output, exports, money balances, and employment. Bernanke and Parkinson (1991) criticize this theory, however, on the grounds that recessions would require to observe a retrace in technology. Kehoe and Prescott (2002), on the other hand, provides evidence from nine major depressions of the 20th century that technology shocks can account for a substantial part of downturns.

[3] For a Cobb-Douglas technology, equation (4) is unambiguously negative $\frac{d(Y_{it}/L_{it})}{d\,\eta_{it}} = \frac{\partial L_{it}}{\partial \eta_{it}} \left(\frac{(\alpha - 1) F^{l}_{it}}{L^{2}_{it}} \right) < 0$.

A third case of interest arises when there are no external effects (ν=0) or unused capital (u_{it}=1) but labor comprises two components: time allocated to production, q_{it}, and time dedicated to maintenance and training, m_{it} (Baily et al., 1996). 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 the production function $q_{it} = e_{it} L_{it}$, hence $m_{it}>0$ when $e_{it} < 1$. Under these assumptions, therefore, there is space for labor hoarding. Due to the existence of rigidities in changing labor in the short run (e.g., fire and hire costs), firms adjust the effort of workers and reassign the labor force to non-productive activities, such as maintenance or training. Hence the following production function is considered $Y_{it} = A_{it}F(K_{it}, e_{it}L_{it})$ and the response of average labor productivity to demand shocks is:

$$\frac{d(Y_{it}/L_{it})}{d\,\boldsymbol{h}_{it}} = \frac{\partial(q_{it}+m_{it})}{\partial \boldsymbol{h}_{it}}\left(\frac{(q_{it}+m_{it})F^{l}_{it} - F_{it}}{(q_{it}+m_{it})^2}\right) \leq 0 \qquad \textbf{(6)}$$

Then, labor productivity could be procyclical when m_{it} is large enough. Introducing varying effort, the response of the employment to a demand shock should be smaller than the corresponding in the standard model. In the particular case of the Cobb-Douglas function, the reaction of labor productivity to a demand shock is:

$$\frac{d(Y_{it}/L_{it})}{d\,\boldsymbol{h}_{it}} = \frac{\partial(q_{it}+m_{it})}{\partial \boldsymbol{h}_{it}}\left(\frac{(\boldsymbol{a}-1)F^{l}_{it} + \boldsymbol{a}(m_{it}/q_{it})F_{it}}{(q_{it}+m_{it})^2}\right) = \frac{\partial(q_{it}+m_{it})}{\partial \boldsymbol{h}_{it}}\left(\frac{(\boldsymbol{a}/e_{it}-1)F_{it}}{(q_{it}+m_{it})^2}\right)$$

The term $\boldsymbol{a}(m_{it}/q_{it})F_{it}$ in the numerator of the right hand side can be larger than $(\boldsymbol{a}-1)F^{l}_{it}$ allowing for the presence of procyclical productivity. This suggests that the greater the proportion of labor assigned to non production activities (i.e., maintenance and training), the greater the probability of finding procyclical productivity. It can also be observed that effort is inversely related to the ratio of non productive activities to production.[4]

In the fourth case we consider, output is produced without external effects or labor hoarding (ν=0 and e_{it} =1) but the production function has increasing returns to scale. In such case, it would be expected that firms vary the effective utilization of inputs proportionally. Then, it can be assumed that the rate of utilization of capital displays a linear relationship with labor demand, so $u_{it}K_{it} = \mathrm{N}L_{it}$. The production function becomes $Y_{it}=A_{it}F(\phi L_{it},L_{it})$ and the response of labor productivity to a demand shock is procyclical:[5]

$$\frac{d(Y_{it}/L_{it})}{d\eta_{it}} = \frac{\partial L_{it}}{\partial \eta_{it}}\left(\frac{L_{it}(dF_{it}/dL_{it}) - F_{it}}{L_{it}^{2}}\right) > 0 \qquad \textbf{(7)}$$

The fifth and final case we consider focuses on external effects as collected in parameter ν>0. In this case there are external economies not associated to input variations that could induce procyclical productivity. These externalities emerge from the increased possibilities of matching among agents that arise in large-size markets. The magnitude of transactions between firms and their customers is the key factor in the transmission of short-run external effects. This hypothesis was first proposed by Caballero and Lyons (1992). Generally, these externalities are captured in the production function through a factor that consider the level of aggregate economic activity. The effect of economic activity on the fluctuations of average labor productivity is clearly positive:

$$\frac{d(Y_{it}/L_{it})}{d\varepsilon_{it}} = \frac{\partial Y_{it}}{\partial Y_{t}}\frac{Y_{it}}{L_{it}} > 0 \qquad \textbf{(8)}$$

Table 1 summarizes the different cases we study and their implications with regards to the sign of the correlation between the fluctuations in average productivity and output.

[4]This hypothesis of procyclical labor productivity has been studied by many authors, among them Fay and Medoff (1985), Aizcorbe (1992), Sbordone (1997) and Burnside et al. (1993).

[5]In the Cobb-Douglas case $dF_{it}/dL_{it} = (\alpha + \beta)(Y_{it}/L_{it})$. This expression is greater than 1 under increasing returns to scale and generates procyclical labor productivity (see Hall, 1990 and Basu, 1996).

Table 1
Cyclical Behavior of Labor Productivity under Alternative Models

Model	Assumptions				Output-productivity correlation
	u_{it}	e_{it}	ν	z_{it}	
Traditional	1	1	0	$\boldsymbol{h}_{it}$	< 0
Technical change	[0,1]	[0,1]	> 0	$\boldsymbol{e}_{it}$	> 0
Labor hoarding	1	[0,1]	0	$\boldsymbol{h}_{it}$	> 0
Increasing scale returns	[0,1]	1	0	$\boldsymbol{h}_{it}$	> 0
External economies	[0,1]	[0,1]	> 0	Y_t	> 0

3. A quick look at the Chilean aggregate evidence

In order to test the alternative explanations of the cyclical fluctuations of average labor productivity (traditional, technical change, labor hoarding, increasing returns to scale, and external economies), we use data of the Chilean industry for the 1979-1997 period. The data were obtained from the National Annual Industrial Survey (ENIA) conducted by the Chilean bureau of statistics (INE) and comprise between 4,000 and 6,000 firms every year. Firms were classified according to the 2nd revision of the International Standard Industrial Classification of economic activities (ISIC), at 4-digit level. The information corresponds to 84 of the 91 sectors included in the database since data inconsistencies prevent us from using seven sectors (deleted sectors are of insignificant economic impact). Figures correspond to sector averages; it would have been preferable to work with firm-level data, but the information was only available for a reduced period of time (1986-94), severely limiting the analysis of economic cycles. Appendix 1 describes the database.

As customary in studies that test cycles in productivity, output is measured by value added (VA) defined as gross output less the total costs of intermediate goods and services plus the net change in inventories. Labor productivity is obtained as the quotient of VA and a measure of labor input (the product of "average total occupation" by "worked days in the year"). Annual average 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). Worked days represent the number of days in which each firm was in activity.

The industrial sector in Chile represents around 18% of GDP in the period of analysis and it accounts for nearly 70% of exports and 15% of employment (Table 2). The relative size of industry is quite stable over the years of the surveys. We split the sample in two sub-periods to test the robustness of the results. The first period 1979-85 is characterized by major structural and sectoral reforms (including market liberalization, privatization, and opening to foreign competition) and the severe recession of 1982-83. The 1986-1997 period is characterized by vigorous, sustained growth and a marked increase in general productivity.

Table 2
Size of the Chilean Industry

	Share of industry in: (in percentage)		
Period	GDP	Employment	Exports
1979-97	17.5	15.5	70.7
1979-85	17.8	14.5	74.4
1986-97	17.3	16.0	68.5

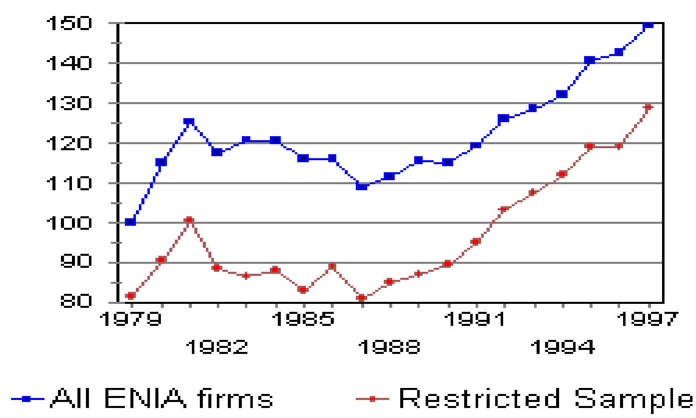
As the Chilean economy underwent deep structural transformations in the period of analysis, relative prices changed dramatically. Relative prices between traded and non-traded goods changed as a result of opening to foreign competition; relative prices of factors and intermediate goods changed as a result of market liberalization; and the relative cost of technology changed as firms were granted access to international markets at stable, competitive exchange rates (see Larraín y Vergara, 2000, for a survey). Consequently, there were significant changes in the incentives faced by firms, but their response was heterogenous. While most branches of the industrial sector boomed, some sectors experienced marked declines in terms of output and use of the different inputs.

Table 3 shows the growth of the Chilean economy and industry in the 1979-97 period. GDP grew on average at around 5.3% while employment expanded at around 3.3%, leading to an average increase in labor productivity of 2% per year. Industrial output and labor productivity grew more moderately at around 4% and 1%, respectively. With regards to the sample of firms used in this paper (dubbed ENIA firms), output growth figures are comparable but employment figures -obtained directly from firms surveyed by ENIA- are markedly lower, leading to an average growth of labor productivity that is similar to countrywide figures. The difference between ENIA and INE employment figures is that the former excludes micro businesses that are labor intensive (less than 10 employees).

Table 3
Evolution of Value Added, Employment and Productivity in the Chilean economy, industry, and ENIA sample firms
Annual growth rate (%) 1979-1997

	Whole Economy	Industry (national accounts)	ENIA sample firms: Weighted average (by value added)	ENIA sample firms: Unweighted Average	ENIA sample firms: Sectors with positive growth	ENIA sample firms: Sectors with negative growth
Value Added	5.3	4.1	3.9	3.8	69	15
Employment	3.3	3.1	1.6	1.5	51	33
Productivity	2.0	1.0	2.3	2.3	66	18

Figure 1
Average Labor Productivity Levels
(All ENIA firms in 1979 = 100)



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 some extent the average of the industrial sector. These sectors are the tobacco, petroleum, copper mining, pulp and paper firms. Figure 1 plots average labor productivity for the complete sample (84 sectors) and a sub sample excluding the five sectors with largest productivity (hereafter called the restricted sample). It can be noted that when excluding those five sectors, average industrial productivity is reduced by about 20%. 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 1986, productivity starts to increase at a steady pace (around 5% per year), justifying the split of the sample in two sub periods (1979-1985) and (1986-1997) for the empirical analysis.

Figure 2
Histograms of Sector Labor Productivity, 1979-1997

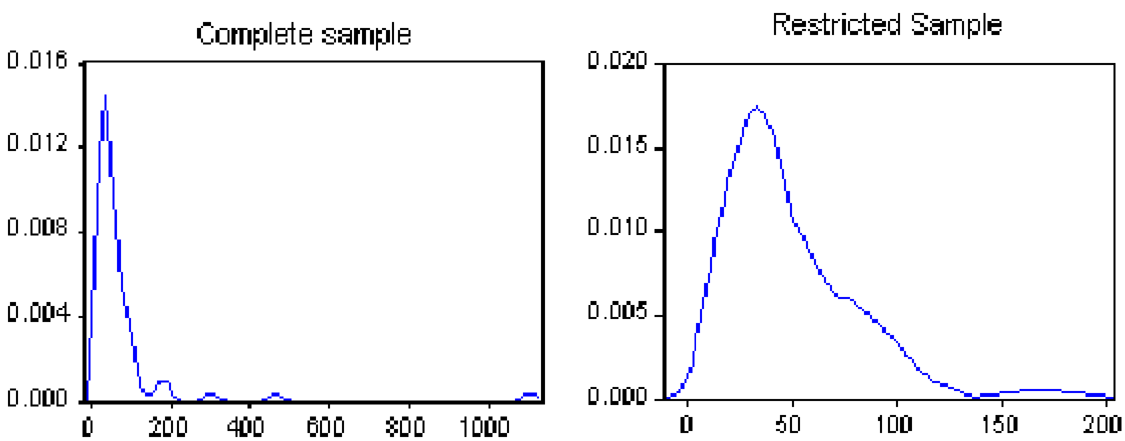


Figure 2 presents histograms of average labor productivity for the complete and restricted samples. These graphs show clearly the large differences in productivity between the five most productive sectors and the rest of the branches. However, productivity heterogeneity persists in the restricted sample, as the corresponding histogram indicates.

The disaggregated data present not only structural heterogeneity but also dynamic heterogeneity. There are significant movements in the relative productivity of the sectors that are masked in aggregate figures. This feature of the data is presented in Table 4, that provides information on the labor productivity transition matrix, that is the frequency of sectors that switched labor productivity levels (relative to the sample average) between

1979 and 1997. When constructing the table, sectors were ordered according to their relative productivity with respect to the average productivity in each of the two years. Five clusters of productivity levels were easily identified. The distribution of sectors by intervals is computed as the percentage of sectors that were in one cluster in 1979 and continued to be in such cluster or moved to different clusters in 1997.

Table 4
Transition Matrix of Normalized Sector Productivity Levels*
Percentage of sectors

	1997				
	0 - 0.5	**0.5 – 1**	**1 - 1.5**	**1.5 - 2**	**2 or more**
0.5 - 1	***33.3***	*50.0*	*10.0*	*0.0*	*6.7*
1 - 1.5	*5.6*	***27.8***	***33.3***	*11.1*	*22.2*
1.5 - 2	*14.3*	*0.0*	*14.3*	***42.9***	*28.6*
2 or more	*0.0*	*0.0*	*0.0*	*37.5*	***62.5***

Note: (*) The productivity of firms was normalized using the industry average (e.g., 1.5-2 means that firms have between 1.5 and 2 times the industry average).

It can be noted that there is substantial mobility among firms, i.e., the number of sectors that remain in its original cluster is low. There were significant changes in the relative productivity of the two least productive clusters. For example, more than 60% of the sectors that in 1979 had average productivity below one half of the industry average in that year increased their relative productivity levels by 1997. Likewise, sectors in the other clusters also changed their relative productivity position.

This evidence is clear in two additional dimensions. First, aggregate figures tend to be distorted by a few very large sectors in which labor productivity is markedly higher than in the rest of the sample. Second, aggregate figures tend to distort our understanding of the dynamics of labor productivity as they smooth out important changes in productivity levels experienced by the different sectors. Both elements suggest the importance of exploring the link between labor productivity and economic fluctuations at the sectoral –instead of the aggregate– level.

4. Evidence from Disaggregated Data

In this section we study the cyclical behavior of average labor productivity in the 84 sectors of our sample using the correlation between detrended measures of labor productivity and value added, as suggested in Section 2. The first step consists in estimating detrended measures of both variables. Although the most popular method of detrending is the Hodrick-Prescott (HP) filter, it presents important limitations. King and Rebelo (1993) provide examples of how measures of persistence, variability, and comovement are distorted when the HP filter is applied to observed time series and to series simulated with real business-cycle models. Harvey and Jaeger (1993) and Cogley and Nason (1995) show that spurious cyclicality can be induced when the HP filter is applied to the level of a random-walk process. Osborn (1995) reports a similar result for a simple moving-average detrending filter. Alternative methods (such as those proposed by Beveridge and Nelson, 1981 and Baxter and King, 1988) present similar drawbacks.

Consequently, it seems reasonable to undertake the analysis using three alternative detrending methods: the linear trend, the HP filter, and a heuristic filter proposed by Rotemberg (1999). The novelty of Rotemberg´s method is that it imposes orthogonality conditions between the cycle and the trend, and between the cycle in time t with cycle in time t-k that reduces the potential problems of spurious cyclicality that may be induced by others filters. The main conclusions of this section are, nevertheless, insensitive to the detrending method applied.

We first explore the cyclical properties of labor productivity and output at the aggregate level. Table 5 presents the correlations between detrended measures of average labor productivity and value added for the whole economy, the industrial sector, and the ENIA firms for the whole period of analysis and the sub-period 1986-1997. As mentioned in the introduction, the Chilean economy shows strong evidence of procyclicality in labor productivity (ranging from 0.45 to 0.63, depending on the detrending method used). This result has been reported in previous studies (e.g., Bergoeing and Soto, 2001) and is particularly pronounced in the sub period 1986-1997 (0.71 to 0.81).

Nevertheless, at the industry level we found the puzzling result that labor productivity is countercyclical. The correlations estimated using national accounts data are negative and large in both periods, being more significant in the whole period than in the 1986-97 sub-period. The correlations calculated using data from ENIA firms weighted by value added suggest that the evidence is mixed and that results are sensitive to the detrending method and the size of firms.

The correlations obtained in the different sectors of the ENIA sample portrays a different and more interesting picture than that of the aggregate sample. The first salient feature is that countercyclical productivity is observed in firms employing more than 50 workers but not in medium and small size firms (between 10 and 50 employees) which, in fact, display strong procyclical productivity. This evidence, which is consistent with the dynamic heterogeneity discussed in the previous section, merits further attention. The second salient feature is that evidence of countercyclical productivity is only found in the 1979-85 period. In the 1986-97 period the data suggest absence of countercyclical productive and, at best, some mild procyclical behavior.

The differences in the correlations obtained using national accounts data and ENIA data are largely due to different figures for industrial employment. As shown in the lower panels of table 5, the cycles of valued added measured by national accounts and ENIA are quite similar (correlations rank from 0.85 and 0.98). On the other hand, the cyclical components of labor productivity measured by the ENIA sample and national accounts are more sensitive to the detrending method and relatively less correlated.

Table 5
Correlation between Labor Productivity and Value Added at the aggregate level

	Hodrick Prescott		Linear Trend		Rotemberg	
	79-97	86-97	79-97	86-97	79-97	86-97
Correlation between average labor productivity and						
Gross Domestic Product (national accounts data)	0.63	0.81	0.60	0.79	0.45	0.71
Industry (national accounts data)	-0.61	-0.30	-0.36	-0.38	-0.70	-0.44
Industry (ENIA sample, value-added weighted)	-0.14	0.05	-0.35	0.30	-0.18	0.29
• Firms with more than 50 employees	-0.42	-0.05	-0.44	0.10	-0.42	0.26
• Firms with between 10 and 50 employees	0.87	0.95	0.90	0.96	0.79	0.94
Correlation between value added in ENIA firms and						
Gross Domestic Product	0.85	0.45	0.88	0.41	0.72	0.10
Industrial value added in national accounts	0.98	0.92	0.99	0.88	0.97	0.85
Correlation between labor productivity in ENIA firms and						
Labor productivity in the Chilean economy	0.44	0.53	0.34	0.44	0.57	0.02
Industrial labor productivity in national accounts	0.68	0.84	0.73	0.90	0.70	0.58

The results obtained at the aggregate level represent the net outcome of countercyclical and procyclical forces that are masked in the aggregate data. Based upon this evidence, a deeper analysis was conducted obtaining labor productivity-output correlations for each sector. Table 6 displays value-added weighted and unweighted averages of the correlations observed in the complete sample. Weighted correlations reproduce the low countercyclicality obtained before. Unweighted correlations, on the other hand, indicate that on average labor productivity is strongly procyclical in the industrial sectors examined. These findings are very similar in the two periods of time and three detrending methods considered.

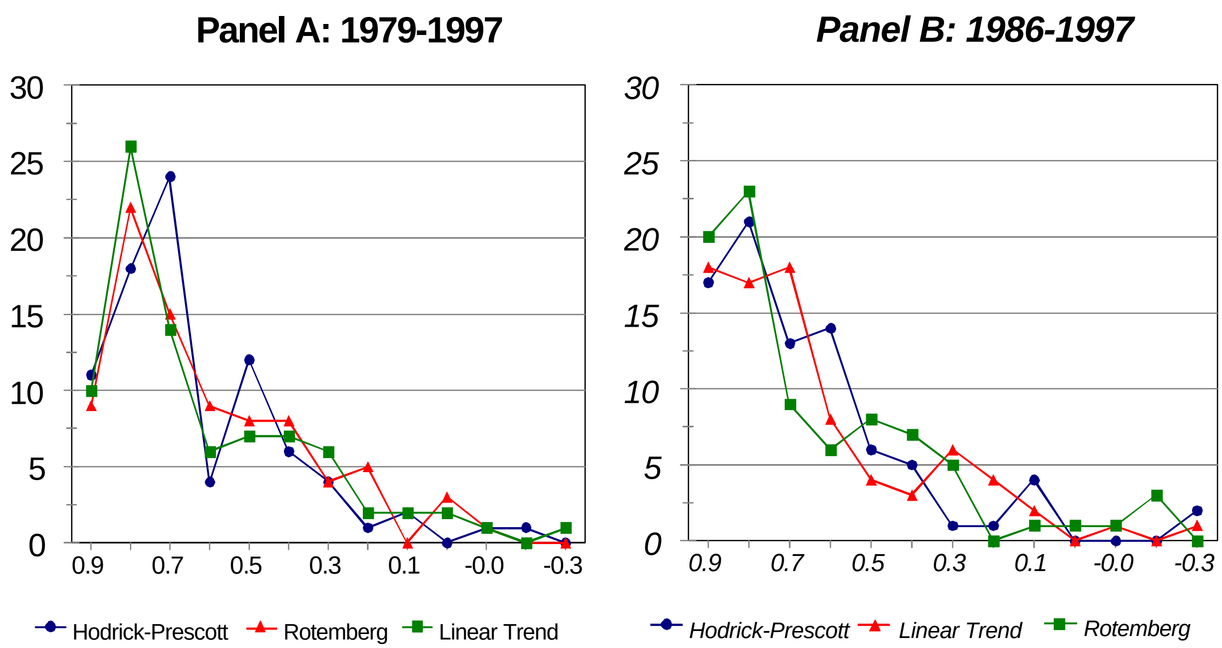
Table 6
Correlations of the cyclical components of labor productivity and value added (ENIA sample)

	Detrending Method		
	Hodrick-Prescott	Linear trend	Rotemberg
Value added weighted correlations			
1979-97	-0.14	-0.36	-0.18
1986-97	0.05	0.30	0.29
Unweighted correlations			
1979-97	0.68	0.66	0.66
1986-97	0.74	0.67	0.69

Figure 3 presents the distribution of correlations between productivity and output for all the detrending methods and time periods. Although there are some slight differences among the moments of higher order of these distributions, all of them reveal procyclical productivity (*corr(xt,yt)>0*) in more than 95% of the 84 sectors analyzed. Between 60% and 70% of the sectors displays strong procyclical productivity, defined as a correlation greater than 0.6 in the period 1986-1997.

In general, correlations obtained with weighted data should be different from the unweighted average of the correlations of each sector, i.e., $corr(\bar{x}_{it}, \bar{y}_{it}) \neq \overline{corr(x_{it}, y_{it})}$. The source of these differences is the divergence between the detrended measures of the aggregated series (productivity and output) and those of the sectoral variables that make up the aggregate. The incidence of each sector in the aggregate cycle also depends on its relative size.

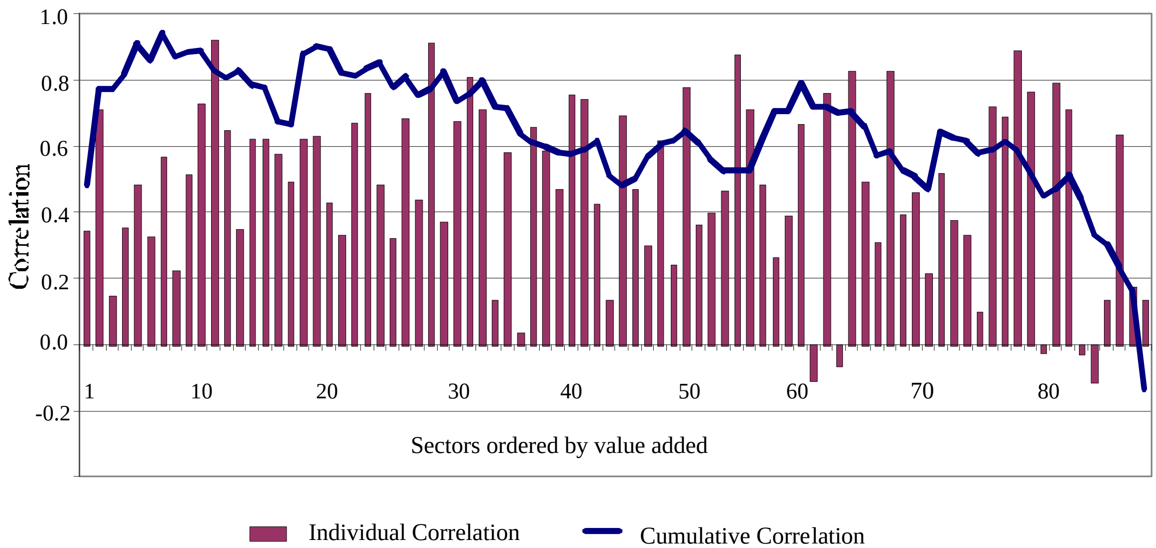
Figure 3
Frequency distribution of labor productivity-output correlations



When studying the time-series evidence on these correlations, an essential characteristic of aggregate business cycles to assess is precisely the presence of sectoral comovement. It would be strange to find different branches of an industry displaying cycles of significantly different intensity and direction. In fact, comovement is fundamental to the definition of business cycles. The NBER identifies recessions or expansions as persistent decreases or increases in output, income, and employment in many sectors of the economy simultaneously. According to Christiano and Fitzgerald (1998), for a measure of aggregate cycle to be valid, there must be comovement between the aggregate dynamics and each of their components.

The comovement measure used in this study is the correlation between the detrended output of each sector and that of the complete sample, *corr(yt,Yt)*, in the complete 1979-1997 period. We used the Hodrick-Prescott filter to remove trends, but alternative detrending methods do not alter the general findings. The correlations –which are shown in Figure 4 in the bar series– are displayed by the value added of the sectors in ascending order. It can be seen that in a significant number of sectors value added presents high correlation with the aggregate index, i.e., they comove. On average, the correlation between the cyclical components of sectoral output and aggregate output cycles is 0.48.[6] A second issue emerging from figure 4 is that the correlation between aggregate value added and labor productivity is distorted by the biggest, more productive industries. The thick line in figure 4 is the cumulative aggregate correlation, which is positive when including most of the sectors but becomes negative once the sectors identified in section 3 are added (tobacco, petroleum, copper mining, pulp and paper). These sectors display low or negative comovement with aggregate cycles. This is an additional evidence of the misleading picture emerging from the use of aggregate productivity indices.

Figure 4
Comovement and cumulative correlations between sector productivity and value added
HP filtered series (1979-97)



[6]Christiano and Fitzgerald (1998) calculate comovement of hours worked in different sectors of the American economy and find that the private sector cycles account for more than 70% of the variance of the sector cycles in the economy. The method used to obtain comovement is, however, different from that used in this study.

5. Testing alternative theories of procyclical labor productivity

The tests of the preceding sections give strong evidence of procyclical productivity in the industrial sectors surveyed by ENIA. In this section we follow the approach developed by Fernald and Basu (1999) to quantify the relative importance of the different explanations of procyclical productivity. First, we extend the model in section 2 to include intermediate inputs in the production function and estimate gross-output production function in log differences at the sector level, that allows for variations in utilization of inputs, imperfect competition, and technical change (as a residual). After estimating these gross-output production functions we aggregate sectors under a value added specification. Aggregation across sectors, however, is not simply the sum of the individual components because it includes a reallocation term that reflects the effect on output growth of differences among sectors in the social values of the marginal product of inputs.[7] Therefore, output growth depends on the distribution of input growth among sectors as well as on their level; if inputs grow rapidly in sectors that have above-average marginal products, output grows rapidly as well. These are qualitative additional effects at the aggregate level which may be important both for estimating sector-level parameters and as powerful amplification mechanisms in their own right.

As a starting point, considered the following gross-output growth equation at the sector level. It relates the log difference in gross output (dy_i) to a revenue-weighted measure of growth in inputs (dx_i), a proxy for variations in capital utilization and effort ($d\mu_i$), and a residual that captures technical change (dt_i). Formally,

$$\begin{aligned} dy_i &= m_i(1-s_{Mi})du + dt_i + m_i dx_i \\ dy_i &= m_i(1-s_{Mi})du + dt_i + m_i\left[s_{Ki}dK_i + s_{Li}dL_i + s_{Mi}dM_i\right] \end{aligned} \qquad \textbf{(9)}$$

the expression in brackets shows that dx is a share weighted average of observed input growth. Appendix 2 shows that μ_i is a markup of price over marginal cost. Perfect competition implies μ_i equals one. The shares s_{Ki}, s_{Li} and s_{Mi} are the total cost of each input divided by gross output. The shares sum to less than one if firms make pure profits.

[7]Fernald and Basu (1999) suggest that this relocation term has been erroneously considered as an external effect in some studies.

Estimation of equation (9) would require an index of capital utilization. Abbott et al (1998) and Fernald and Basu (1999) suggest to use as a proxy the growth rate in hours worked. Hence, we estimate:

$$dy_i = c + m_i dx_i + adh_i + dt_i \tag{10}$$

where dh is the growth rate in hours worked. Although ENIA data does not include hours worked, additional data on hours worked from the employment surveys of 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.

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.

We applied this methodology to 59 sectors of the ENIA sample that represent on average the 86% of the industry gross output in the 1979-1997 period. We excluded 26 sectors from the database because irregularities in the data on costs made estimations unreliable[8]. Equation (10) was estimated for each sector. As noted by Fernald and Basu (1999), 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 five groups and the constant and the utilization proxy were restricted to be equal across groups.[9] Each system was estimated using three-stage least squares to avoid correlation between technology shocks and inputs across sectors. The instruments include all the 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.

[8]We excluded sectors the residuals clasification in each group (i.e., those labeled “not elsewhere classified”), canning of seafood, some textiles, furs, non-metal furniture, chemicals, pottery and china, manufacture of tools, and shipbuilding.

[9]The groups were formed according to their 2-digit level ISIC classification. Consequently we formed groups for categories 31 (15 sectors), 32 to 34 (14 sectors), 35 to 37 (13 sectors), and 38 to 39 (17 sectors). See appendix 1 for a description of each sector.

After estimating equation (10) 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 following aggregation equation to decompose aggregate productivity into a technological component plus various non-technological components, including the effects of markups and reallocation of inputs:

$$dv = \overline{m}^{V} dx^{V} + du + R + dt^{V} \qquad \textbf{(11)}$$

where dv is the aggregate growth in value added, $\overline{m}^{V}$ is the average markup across firms, dx^{V} is the weighted-average growth of inputs, du is the weighted average of utilization rates at the sector level, R represents reallocation of inputs between firms, and dt^{V} is the weighted average of sector technical change.[10]

Expressing productivity growth as $dp = dv - dx^{V}$, equation (11) becomes:

$$dp = (\overline{m}^{V} - 1)dx^{V} + du + R + dt^{V} \qquad \textbf{(12)}$$

Equation (12) shows that aggregate growth in total measured factor productivity is a combination of the growth of inputs in sectors with different markups, the change in labor effort and capital utilization, input reallocation, and technical change, respectively.

The results for the 1979-1997 period and the 1986-1997 subperiod are presented in Table 7 (details on the estimation are in Appendix 3). 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. It accounts for nearly 50% of productivity growth in the 1979-97 period and almost 70% in the 1986-97 period. Reallocation of resources among sectors was important in the both periods, but less so in the 1986-1997 period. Instead, in this shorter and more stable period internal increasing returns gained weight as determinants of the growth in productivity. Variations in utilization were insignificant in both samples, perhaps reflecting the fact that we are reporting averages that tend to net out cyclical variations. In addition, the volatility of productivity is substantially higher in the 1979-1985 period than in the 1986-1997 period, when measured by standard deviations, largely as a result of higher volatility in technical changes.

[10]The aggregate output measure is presented in value added terms rather than in gross terms and is obtained as a difference between gross output and materials. For details on the computation of aggregate variables see Fernald and Basu (1999).

Table 7
Decomposition of the aggregate growth in productivity
average annual growth rates

	Change in observed productivity dp	Change in markups $(\overline{m}^V - 1)dx^V$	Change in labor effort and capital utilization du	Technical change dt^V	Reallocation of inputs R
			1979-1997		
Average	5.1%	0.8%	0.0%	2.5%	1.8%
Standard deviation	0.219	0.008	0.002	0.191	0.087
			1986-1997		
Average	5.3%	1.1%	0.0%	3.5%	0.6%
Standard deviation	0.040	0.004	0.002	0.078	0.086
			1979-1985		
Average	4.8%	0.3%	0.0%	0.8%	3.7%
Standard deviation	0.525	0.015	0.002	0.385	0.089

Table 8 presents the correlations between these computed sources of productivity shocks, computed for the whole sample. As expected, there is evidence of strong procyclicality in measured productivity and technical change. The correlation between inputs and technology is positive but not strong. These results give additional support to the notion that technological shocks are the main source of business cycles, as proposed by the RBC literature. However the evidence in Tables 7 and 8 suggests that the latter do not account for the whole story in the explanation of the dynamics of productivity and, consequently, it would be unwarranted to model macroeconomic cycles as solely depending on technology shocks. In particular, input reallocation and imperfect competition have an increasingly important role as sources of fluctuations in economic activity.

Table 8
Correlations among the determinants of average productivity
(59 sectors of the ENIA survey)

	dp	dx^V	dv	dx^V
dp	1			
dx^V	0.357	1		
dv	0.998	0.410	1	
dt^V	0.916	0.297	0.912	1

6. Conclusions

This paper studies the dynamics of productivity during economic cycles in Chilean in the 1979-1997 period. The data confirms the widespread, puzzling regularity that average productivity tends to rise during booms and reduce during recessions. This behavior goes against traditional macroeconomic theory which suggests that, if the law of diminishing returns to factors holds, productivity should be countercyclical. We show that for the vast majority of the 84 industrial sectors we study, productivity is significant and highly procyclical.

The study first unveils the importance of using disaggregated data. We found that aggregate data from national accounts on the industrial sector would suggest that productivity is countercyclical. This result arise from distortions induced by a few very large sectors in which labor productivity is markedly higher and behaves differently than in the rest of the sectors. Aggregate figures distort our understanding of the dynamics of labor productivity as they smooth out important changes in productivity levels experienced by these different sectors. Sector data show that 95% of the 84 sectors we study are procyclical; comovement of detrended value added in these sectors and detrended GDP is above 0.6.

The second part of this paper quantifies the determinants of productivity changes. Several theories had been advanced to account for the observed procyclical behavior of productivity, including procyclical technology shocks, imperfect competition and increasing returns, variable capital utilization and labor hoarding, and externalities in the production process derived from reallocation of capital and labor. Following a methodology proposed by Fernald and Basu (1999) we decompose observed productivity growth accordingly to these four theories.

These results suggest that technical changes are the main explanation of the dynamics of productivity in the Chilean industry. It accounts for nearly 50% of productivity growth in the 1979-97 period and almost 70% in the 1986-97 period. Reallocation of resources among sectors was important in the both periods, but less so in the 1986-1997 period. Instead, in this shorter and more stable period internal increasing returns gained weight as determinants of the growth in productivity. Variations in utilization were insignificant in both samples.

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Appendix 1
ISIC - International Standard Industrial Classification of All Economic Activities, Revision 2, at three and four-digit levels.

311 Food	3111 Slaughtering, preparing and preserving 3112 Manufacture of dairy 3113 Canning and preserving of fruits 3114 Canning, preserving and processing of fish, crustacea and similar foods 3115 Manufacture of vegetable and animal oils 3116 Grain mill 3117 Manufacture of bakery 3118 Sugar factories 3119 Manufacture of cocoa, chocolate and sugar 3121 Manufacture of food products not elsewhere 3122 Manufacture of prepared animal
313 Beverages	3131 Distilling, rectifying and blending 3132 Wine 3133 Malt liquors 3134 Soft drinks and carbonated waters industries
314 Tobacco	3140 Tobacco manufactures
321 Textiles	3211 Spinning, weaving and finishing 3212 Manufacture of made-up textile goods except wearing 3213 Knitting 3214 Manufacture of carpets 3215 Cordage, rope and twine 3219 Manufacture of textiles not elsewhere classified
322 Wearing apparel, except footwear	3220 Manufacture of wearing apparel, except footwear
323 Leather	3231 Tanneries and leather 3232 Fur dressing and dyeing 3233 Manufacture of products of leather and leather substitutes, except footwear and wearing apparel
324 Footwear, except rubber or plastic	3240 Manufacture of footwear, except vulcanized or molded rubber or plastic footwear
331 Wood products, except furniture	3311 Sawmills, planing and other wood 3312 Manufacture of wooden and cane containers and small cane 3319 Manufacture of wood and cork products not elsewhere classified
332 Furniture, except metal	3320 Manufacture of furniture and fixtures, except primarily of metal
341 Paper and products	3411 Manufacture of pulp, paper 3412 Manufacture of containers and boxes of paper 3419 Manufacture of pulp, paper and paperboard articles not elsewhere classified
342 Printing and publishing	3420 Printing, publishing and allied industries
351 Industrial chemicals	3511 Manufacture of basic industrial chemicals except 3512 Manufacture of fertilizers 3513 Manufacture of synthetic resins, plastic materials and man-made fibers except
352 Other chemicals	3521 Manufacture of paints, varnishes 3522 Manufacture of drugs 3523 Manufacture of soap and cleaning preparations, perfumes, cosmetics & other toilet 3529 Manufacture of chemical products not elsewhere classified
353 Petroleum refineries	3530 Petroleum refineries

354 Miscellaneous petroleum and coal products	3540 Manufacture of miscellaneous products of petroleum and coal
355 Rubber products	3551 Tires and tubes 3559 Manufacture of rubber products not elsewhere classified
356 Plastic products	3560 Manufacture of plastic products not elsewhere classified
361 Pottery, china, earthenware	3610 Manufacture of pottery, china and earthenware
362 Glass and products	3620 Manufacture of glass and glass products
369 Other non-metallic mineral products	3691 Manufacture of structural clay 3692 Manufacture of cement, lime 3699 Manufacture of non-metallic mineral products not elsewhere classified
371 Iron and steel	3710 Iron and steel basic industries
372 Non-ferrous metals	3720 Non-ferrous metal basic industries
381 Fabricated metal products	3811 Manufacture of cutlery, hand tools and general 3812 Manufacture of furniture and fixtures primarily of 3813 Manufacture of structural metal 3819 Manufacture of fabricated metal products except machinery and equipment not - elsewhere classified
382 Machinery, except electrical	3821 Manufacture of engines 3822 Manufacture of agricultural machinery 3823 Manufacture of metal and woodworking machinery 3824 Manufacture of special industrial machinery and equipment except metal and - woodworking machinery 3825 Manufacture of office, computing and accounting machinery 3829 Machinery and equipment except electrical not elsewhere classified
383 Machinery, electric	3831 Manufacture of electrical industrial machinery and apparatus 3832 Manufacture of radio, television and communication equipment 3833 Manufacture of electrical appliances 3839 Manufacture of electrical apparatus and supplies not elsewhere classified
384 Transport equipment	3841 Shipbuilding 3842 Manufacture of railroad 3843 Manufacture of motor 3844 Manufacture of motorcycles 3845 Manufacture of 3849 Manufacture of transport equipment not elsewhere classified
385 Professional and scientific equipment	3851 Manufacture of professional and scientific, and measuring and controlling equipment, not elsewhere classified 3852 Manufacture of photographic and optical goods 3853 Manufacture of watches and clocks
390 Other manufactured products	3901 Manufacture of jewelry and related 3902 Manufacture of musical instruments 3903 Manufacture of sporting and athletic goods 3909 Manufacturing industries not elsewhere classified

Appendix 2
Mathematical derivations[11]

(a) The link between markups and returns to scale

Consider the following gross output general production function of firm *i*, Y_i:

$$Y_i = F^i(\tilde{K}_i, \tilde{L}_i, M_i, T_i) \qquad \textbf{(A1)}$$

where $\tilde{K}_i = u_i K_i$ and $\tilde{L}_i = e_i L_i = e_i N_i H_i$ as in equation (1). The index *t* has been omitted for simplicity. Employment is measured as total hours worked defined as the product of number of employees multiplied by hours worked per employee. *Tì* is and index of technology, that is included to capture a corrected Solow residual in the empirical estimations.

Let the firm's production function *Fi* be locally homogeneous degree g_i in total inputs. Then, constant returns implies that $g_i = 1$. Returns to scale can be written in two useful equivalent forms. First, returns to scale equal the sum of output elasticities:

$$g_i = \frac{F_1^i \tilde{K}_i}{Y_i} + \frac{F_2^i \tilde{L}_i}{Y_i} + \frac{F_3^i M_i}{Y_i} \qquad \textbf{(A2)}$$

where F_J^i denotes the derivative of the production function with respect to the Jth element. Second, if firms minimize costs, the local degree of returns to scale is the inverse of the elasticity of costs with respect to output:

$$g_i(Y_i) = \frac{C_i(Y_i)}{Y_i C_i^{'}(Y_i)} = \frac{C_i(Y_i)/Y_i}{C_i^{'}(Y_i)} = \frac{AC_i}{MC_i} \qquad \textbf{(A3)}$$

where $C_i(Y_i)$ is the cost function of firm *i*, *ACi* is the average cost, and *MCi* is the marginal cost.

It is assumed that firms charge a price P_i that is a markup m_i over marginal cost: $m_i = \frac{P_i}{MC_i}$. The markup, a behavioral parameter, and returns to scale, a property of the production function, a strongly related. This link becomes clear after writing equation (A3) as:

[11] This appendix is based on Fernald and Basu (1999).

$$g_i(Y_i) = \frac{C_i(Y_i)}{Y_i C_i^{'}(Y_i)} = \frac{P_i}{C_i^{'}(Y_i)} \frac{C_i(Y_i)}{P_i Y_i} = m_i(1 - s_{pi}) \quad \textbf{(A4)}$$

where s_{pi} is the share of pure economic profit in gross revenue. From (A4) it is clear that if economic profits are small (or zero in perfect competition) markups tends to be equal to returns to scale.

b. Derivation of equation (9)

Following Hall (1990), equation (A1) is expressed in first differences in logs,

$$dy_i = \frac{F_1^i \tilde{K}_i}{Y_i} d\tilde{k}_i + \frac{F_2^i \tilde{L}_i}{Y_i} d\tilde{l}_i + \frac{F_3^i M_i}{Y_i} dm_i + dt_i \quad \textbf{(A5)}$$

Cost minimization puts additional structure to this equation (Hall, 1990). If firms take the price of all the inputs as given, the first order conditions for cost minimization are,

$$P_i F_J^i = m_i P_{Ji} \quad \textbf{(A6)}$$

where P_{ji} is the price of input J. Then firms minimize costs equalizing the value of marginal product of each input to the corresponding price plus the markup.

Equation (A6) allows to write output elasticities as the product of the markups multiplied by the share of the expenditure on each input divided by total revenue (s_{Ji}),

$$F_J^i = m_i \frac{P_{Ji} J_i}{P_i Y_i} = m_i s_{Ji} \quad \textbf{(A7)}$$

Inputs shares sum to less than one in case firms make pure profits. Substituting output elasticities in (A5),

$$dy_i = m_i \left(s_{Ki} d\tilde{k}_i + s_{Li} d\tilde{l}_i + s_{Mi} dm_i \right) + dt_i \quad \textbf{(A8)}$$

$$dy_i = m_i \left[s_{Ki}(dk_i + dz_i) + s_{Li}(dn_i + dh_i + de_i) + s_{Mi} dm_i \right] + dt_i \quad \textbf{(A9)}$$

$$dy_i = m_i\left[s_{Ki}dk_i + s_{Li}(dn_i + dh_i) + s_{Mi}dm_i\right] + m_i(1 - s_{Mi})\left[\frac{s_{Ki}dz_i + s_{Li}de_i}{(1 - s_{Mi})}\right] + dt_i \qquad \textbf{(A10)}$$

If dx_i is a share weighted average of observed input growth, and du_i a weighted average of unobserved variations in capital and labor utilization rates, it is obtained the estimating equation (9),

$$dy_i = m_i dx_i + m_i(1 - s_{Mi})du_i + dt_i \qquad \textbf{(A11)}$$

c. Conversion to value added

Basu and Fernald (1999) define the growth rate in a firm's value added dv_i as:

$$dv_i = \frac{dy_i - s_{Mi}dm_i}{1 - s_{mi}} \qquad \textbf{(A12)}$$

The growth in valued added is then calculated by subtracting from gross output the revenue share weighted contribution of intermediate goods. Replacing (A12) in (A11):

$$dv_i = m_i(dx_i^V + du_i) + (m_i - 1)\frac{s_{Mi}}{1 - s_{Mi}}dm_i + \frac{dt_i}{1 - s_{Mi}}, \qquad \textbf{(A13)}$$

where $dx_i^V = \frac{s_{Ki}}{1 - s_{Mi}}dk_i + \frac{s_{Li}}{1 - s_{Mi}}dl_i = s_{Ki}^V dk_i + s_{Li}^V dl_i$.

Equation (A13) implies that the growth in valued added 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 and this affect value added growth. It is possible that value added growth could be a function of primary input growth alone, in case that intermediate inputs would be equal to primary input growth. Basu and Fernald (1999) prove that (A13) can be rewritten as,

$$dv_i = m_i^V dx_i^V + (m_i^V - 1)\left[\frac{s_{Mi}}{1 - s_{Mi}}\right](dm_i - dy_i) + m_i^V du_i + dt_i^V \qquad \textbf{(A14)}$$

where $m_i^V = m_i \frac{1 - s_{Mi}}{1 - m_i s_{Mi}}$, and $dt_i^V = \frac{dt_i}{1 - m_i s_{Mi}}$.

d. Aggregation over sectors. Derivation of equation (11)

Aggregate inputs are defined as the simple sum of sector levels quantities. The aggregate value added growth rate is defined as follows,

$$dv = \sum_{i=1}^{N} w_i dv_i \tag{A15}$$

where w_i is the sector's share of nominal value added in the industry, $w_i = \frac{P_i^V V_i}{P^V V}$. Basu and Fernald (1999) demonstrate that the introduction of (A15) in (A14) results in their basic aggregation equation

$$dv = \overline{m}^V dx^V + du + R + dt^V \tag{A16}$$

where $dx^V = s_L^V dl + s_K^V dk$, $\overline{m}^V = \sum_{i=1}^{N} w_i m_i^V$, $du = \sum_{i=1}^{N} w_i m_i^V du_i$, $dt^V = \sum_{i=1}^{N} w_i dt_i^V$. This equation is identical to equation (11) in the text. R represents various reallocation effects detailed in Fernald and Basu (1999).

Appendix 3

Econometric Results (59 sectors)

This appendix presents the detailed results of the estimations of sector equation (10). En each of the 4 systems estimated, C(1) is a sector common constant (c), C(2) is the utilization proxy coefficient (α), the following coefficients represent sector-specific markups (μi).

System: S31

Estimation Method: Three-Stage Least Squares. Sample: 1979-1997

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.006905	0.003982	1.733976	0.0842
C(2)	0.099697	0.049968	1.995226	0.0472
C(3)	0.628925	0.108401	5.801833	0.0000
C(4)	0.850975	0.087577	9.716908	0.0000
C(5)	1.286880	0.098213	13.10295	0.0000
C(6)	1.032605	0.099553	10.37243	0.0000
C(7)	0.583931	0.130107	4.488078	0.0000
C(8)	1.171380	0.127533	9.184928	0.0000
C(9)	0.736292	0.237519	3.099932	0.0022
C(10)	0.998314	0.163203	6.117011	0.0000
C(11)	0.977029	0.187615	5.207612	0.0000
C(12)	1.149146	0.083458	13.76924	0.0000
C(13)	1.459356	0.239943	6.082092	0.0000
C(14)	1.591287	0.131932	12.06139	0.0000
C(15)	1.532818	0.345524	4.436208	0.0000
C(16)	1.031971	0.185831	5.553271	0.0000
C(17)	1.749238	1.817766	0.962301	0.3369
Determinant residual covariance		8.37E-38		

Sectors included: 3111, 3112, 3113, 3115, 3116, 3117, 3118, 3119, 3121, 3122, 3131, 3132, 3133, 3134, 3140

System: S32A34
Estimation Method: Three-Stage Least Squares. Sample: 1979-1997

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.006291	0.004207	1.495260	0.1363
C(2)	-0.031149	0.050546	-0.616256	0.5384
C(3)	1.801527	0.218966	8.227418	0.0000
C(4)	0.835530	0.217486	3.841773	0.0002
C(5)	1.626374	0.142964	11.37612	0.0000
C(6)	1.182113	0.077854	15.18374	0.0000
C(7)	1.525778	0.191965	7.948225	0.0000
C(8)	0.605052	0.131963	4.585003	0.0000
C(9)	1.210732	0.090235	13.41749	0.0000
C(10)	1.135918	0.089184	12.73675	0.0000
C(11)	1.284919	0.209917	6.121081	0.0000
C(12)	1.319652	0.133812	9.862002	0.0000
C(13)	1.363034	0.162363	8.394998	0.0000
C(14)	0.531341	0.348577	1.524314	0.1289
C(15)	0.578666	0.095307	6.071590	0.0000
C(16)	1.309427	0.182862	7.160737	0.0000
Determinant residual covariance		2.72E-34		

Sectors included: 3211, 3213, 3214, 3215, 3220, 3231, 3233, 3240, 3311, 3312, 3319, 3411, 3412, 3420.

System: S35A37
Estimation Method: Three-Stage Least Squares. Sample: 1979-1997

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.014978	0.011948	1.253600	0.2114
C(2)	0.021540	0.055998	0.384653	0.7009
C(3)	1.304543	0.142789	9.136172	0.0000
C(4)	0.623189	0.153083	4.070928	0.0001
C(5)	1.129517	0.240412	4.698267	0.0000
C(6)	1.398941	0.189398	7.386240	0.0000
C(7)	1.867232	0.106799	17.48367	0.0000
C(8)	0.602460	0.108632	5.545891	0.0000
C(9)	2.556880	0.363683	7.030515	0.0000
C(10)	0.809605	0.157044	5.155261	0.0000
C(11)	0.620594	0.271013	2.289905	0.0230
C(12)	0.775432	0.221109	3.507007	0.0006
C(13)	1.499304	0.228386	6.564776	0.0000
C(14)	1.420315	0.120404	11.79624	0.0000
C(15)	0.459789	0.093314	4.927304	0.0000
Determinant residual covariance		3.05E-30		

Sectors included: 3513, 3521, 3522, 3523, 3529, 3530, 3540, 3559, 3692, 3696, 3699, 3710, 3721.

System: S38A39
Estimation Method: Three-Stage Least Squares. Sample:1979-1997

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.006267	0.006702	0.935056	0.3506
C(2)	0.149642	0.092471	1.618254	0.1068
C(3)	1.638928	0.121921	13.44253	0.0000
C(4)	0.869820	0.113686	7.651096	0.0000
C(5)	1.004483	0.199339	5.039061	0.0000
C(6)	1.857424	0.134684	13.79095	0.0000
C(7)	1.889738	0.084281	22.42177	0.0000
C(8)	1.440966	0.081535	17.67294	0.0000
C(9)	1.214983	0.132300	9.183513	0.0000
C(10)	2.324578	0.367646	6.322877	0.0000
C(11)	1.626479	0.348418	4.668183	0.0000
C(12)	1.524377	0.111055	13.72631	0.0000
C(13)	0.679841	0.135334	5.023427	0.0000
C(14)	1.473447	0.138227	10.65964	0.0000
C(15)	1.046788	0.385342	2.716516	0.0071
C(16)	1.047086	0.059845	17.49668	0.0000
C(17)	1.758995	0.257648	6.827133	0.0000
C(18)	1.612250	0.860439	1.873754	0.0621
Determinant residual covariance		1.62000000e-34		

Sectors included: 3812, 3814, 3815, 3819, 3822, 3823, 3829, 3831, 3832, 3833, 3839, 3843, 3844, 3849, 3852, 3909.

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