Total Factor Productivity: Exploring firms' dynamics and heterogeneity over the business cycle

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Abstract

This paper analyzes plant-level total factor productivity (TFP) for Chilean manufacturing firms over the business cycle. Decomposing the aggregate productivity, net entry contributes to productivity growth on average around 30% and continuing firms around 70%. However, net entry contributes exclusively in the recovery years directly following drops (on average above 50%), while in the remaining growth periods this growth comes exclusively from continuing firms. In contrast, the TFP declines in 1997-1998 and 2002-2004 start with a big negative contribution from continuing firms, while afterwards net entry plays a bigger role. In both cases, the continuing firms' contribution to TFP growth and decrease comes mainly from within plants restructuring. The net entry's contribution comes from both entering and exiting without a clear pattern. Further, TFP growth does not spread evenly across sectors, but is an unbalanced process following a mushroom pattern over time (in Harberger´s sense) for all years considered. Overall, the relative importance of the different sectors both in growth and decline periods considerably differs over time, where industries changed from winners to losers regularly.

Keywords: Total factor productivity, heterogeneity, entry and exit, firm and industry level productivity, productivity decomposition.

JEL Classification Codes: L16, L60, O30, O47

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1 Introduction

Understanding the total factor productivity (TFP) is a long-standing problem in economics. TFP is the part of production that is not explained by the amount of used inputs, in general labor and capital. In that sense it is a residual which is determined by the efficiency and intensity with which these inputs are combined. It is interesting to study fluctuations in productivity because there is a broad consensus that TFP, once differences in capital stock and the quality as well as quantity of labor are controlled, accounts for a big fraction (more than half) of the differences in income per capita across countries and their long-term growth rate which affects the welfare of nations (see Hall and Jones 1999, Caselli 2005).[3] Evidence shows that TFP is procyclical, i.e., it increases in booms and falls during recessions (Caballero, 1992).[4] TFP is further known to be heterogeneous, with differences depending on firm age and size, and conditional on exporting, location (Syverson, 2011).

Thanks to the growing availability of detailed data, a very wide literature on firm and plant-level productivity dynamics has analyzed the microeconomic aspects of aggregate productivity growth. There are large and persistent productivity differences among production units, even when comparisons are made within relatively homogeneous sectors (Syverson 2011; Foster, Haltiwanger and Syverson 2008, among others). This suggests that productivity gains can be obtained via two channels: (1) efficiency improvements of continuing firms through either within-plant productivity growth (such as technological change, learning and renewing capital) or by resource reallocation to relatively more efficient continuing production units (relatively productive plants expand market share); and (2) Shumpeterian creative destruction (entry and exit of plants).

However, the literature is ambiguous about the importance of each channel through which aggregate productivity changes materialize. For instance, Foster, Haltiwanger, and Krizan (2001) show that continuing firms account for 75 percent of U.S. aggregate productivity growth, while net entry plays a minor role. In contrast, Brandt, Van Biesebroeck, and Zhang (2012) show that net entry is the most important component of aggregate productivity growth (accounting for 72 percent) in China. Asturias et al (2020), using plant-level data from Chile and Korea, quantitatively measure the relative importance of both margins (net entry vs continuing plants' productivity gains) during periods of

[3] See also Klenow and Rodriguez-Clare (1997); and Caselli and Coleman (2006), among others.
[4] See also Kehoe and Prescott (2002) and Solimano and Soto (2006) for additional evidence for developed and developing countries.

rapid and slow GDP growth. They find that net entry is more important in periods of rapid growth (with an average contribution of 54 percent) but it is less important in periods of slow growth (with an average contribution of just 26 percent).

This paper studies the contributions of both margins (net entry and TFP gains of continuing plants) over the whole business cycle, i.e. not only periods of slow and high growth, but also recessions. We compute TFP decompositions using a recent method for plant-level TFP estimation by Ghandi, Navarro and Rivers (2020). We further analyze the importance of industry heterogeneity in the contribution on TFP gains/losses during different phases of the business cycle. To do so we implement the methodology developed by Harberger (1998) which provides a graphical summary of the pattern of industrial productivity growth by sectors.

Several papers analyze the contribution of productivity dynamics and resource reallocation for Chile. In particular, Levinsohn and Petrin (2002) identify reallocation effects in Chile using data for 1979-86. Pavcnik (2002) studies the effects of a trade reform on the behavior of within-plant productivity growth. In particular, TFP of continuing plants in import competing sectors grows considerably faster than plants in export oriented or non-traded sectors after trade was liberalized. Alvarez and López (2005) compare the performance of exporters and non-exporters and find evidence of self-selection into export markets. Plant TFP increases after plants begin to export, which is consistent with learning by exporting. Closely related to our paper, using Chilean data of the 1980s and 1990s, Bergoeing, Hernando and Repetto (2006), Bergoeing and Repetto (2006), and Bergoeing, Hernando and Repetto (2010) find that exiting plants experience a productivity decrease prior to exit, and that entering survivors quickly improve their productivity. Further, more efficient plants are less likely to fail. These effects were more pronounced in the 1990s than in the 1980s. Finally, the entry of new, more productive units explains most of these reallocation gains. The contribution of within-plant productivity growth is only positive in the 1990s, potentially because market oriented structural reforms in the late 1970s and early 1980s have a delayed effect on the economy. Further, aggregate TFP and GDP per capita move together (Bergoeing and Repetto, 2006). INCORPORATE Oberfield (2013) studies Chile during the crisis in the early 80s and find that reduced capital utilization played a substantial role, accounting for 25-50 percent of the decline in measured TFP.

These papers show reallocation effects in Chile using data only for 1980s and 1990s with special focus on the 1979-86 reforms period and the well-known golden period of productivity growth (1986-1997). Only few papers carefully analyze the micro-dynamics of the period 1995-2007 in which Chile featured a positive GDP growth due to factor accumulation but either a TFP decline or poor performance depending on the estimations (Caballero, Engel and Micco, 2004). Furthermore, among these papers, none analyzes the dynamics for sub-periods including the Asian Crisis, 1997-1999, and the recession 2001-2003.

Using the ENIA (Annual National Industrial Survey) for the period between 1995 and 2007, we estimate TFP at firm and industry level. We focus on this period because only this period allows for a panel, which is needed to properly estimate plants' capital (a key variable to estimate TFP). Decomposing the growth of the total factor productivity into its contribution from continuing plants and entry and exit, we find that the contribution from net entry is larger in high growth periods. Further, in line with Harberger (1998), few sectors are responsible for most of the TFP growth in expansions and the decline in recession, and the remaining sectors, consisting of TFP winners and losers, offset each other's contribution to TFP changes. Finally, the relative importance of the different sectors in their contribution changes over time.

The contribution of this paper is threefold: first, we update previous results about estimation and analysis of productivity growth for Chile employing improved methods for the period 1995-2007. For this period, we confirm some findings in Bergoeing, Hernando and Repetto (2006), Bergoeing and Repetto (2006), and Bergoeing Hernando and Repetto (2010) previously described, but in addition discriminating periods of high and low, and positive and negative growth. In comparison to Asturias et al (2020), we explicitly estimate plant-level TFP with the GNR method rather than approximate it by the industry-level factor cost shares in form of the Solow residual and analyze the TFP decomposition over the whole business cycle rather than comparing different positive growth periods. Finally, to the best of our knowledge, we are the first to implement Harberger's (1998) sunrise-sunset decomposition diagrams based on firm level TFP estimates.

The remainder of the paper is structured as follows: Section 2 describes the theoretical framework and the estimation of the production function. Section 3 discusses the used data and provides descriptive statistics of the underlying variables. Section 4 presents the TFP estimation and discusses plants' performance by size and industry. We decompose the TFP growth over the business cycle in Section 5 and by industry in Section 6. Finally, Section 7 concludes and discusses possible extensions.

2 Estimation of TFP

TFP is typically estimated from a Cobb-Douglas production function (see e.g. Olley and Pakes, 1996, Levinsohn and Petrin, 2013, and Ackerberg Caves and Frazer, 2015)

$$Y_{it} = A_{it} K_{it}^{\beta_{jk}} L_{it}^{\beta_{jl}} M_{it}^{\beta_{jm}} \quad (1)$$

where Y_{it} denotes firm i's production in period t; K_{it}, L_{it} *and* M_{it} are capital, labor and raw materials (intermediate inputs), respectively and β_{jk}, β_{jk}, and , β_{jk} are the respective factor intensities. Note that there is a production function for each sector indexed by the subscript *j*. A_{it} denotes the aggregate productivity of firm i in period t and is formally known as the firm's Hicks neutral efficiency level in the studied period. The marginal product of all factors increases simultaneously (Arnold, 2005). Productivity consists of two components: an *expected* productivity shock specific to the firm denoted by ω_{it} and a *not expected* one denoted by μ_{it}.[5]

Applying logarithm to (1), with small caps denoting logarithms, leads to the following linear production function:

$$y_{it} = \beta_0 + \beta_{jk} k_{it} + \beta_{jl} l_{it} + \beta_{jm} m_{it} + \omega_{it} + \mu_{it}. \quad (2)$$

Since ω_{it} is observed by the firm it might affect its decisions about the use of inputs, the investment and whether to stay in the industry. μ_{it}, on the other hand, is unobserved and thus does not influence the firm's decisions (Van Beveren, 2012). Alternatively, μ_{it} can represent a measurement error and consequently increase the variance of the production (Coublucq, 2013).

Estimating equation (2) by Ordinary Least Squares (OLS) would lead to skewed and inconsistent estimates since the optimal input choice is usually correlated with the observable productivity shock ω_{it}. The main potential problem when estimating a production function is endogeneity (simultaneity). It arises since ω_{it} , which is known by the firm, but unknown to the econometrician, is used to determine the level of inputs used in the production process of the firm (Griliches and Mairesse, 1995).[7] As the effect is attributed to the observable variables – capital, labor and materials – the coefficients tend to be biased upwards. However, it can also happen that more productive firms need fewer inputs to produce the same amount of product as another firm, so in this case the coefficients are biased downwards.

The following widely used methods deal with the aforementioned problems. First, Olley and Pakes (1996) use the firm's investment decision as a proxy for unobserved productivity shocks (to deal with simultaneity) and generate an exit rule (to deal with the sample selection). The monotonicity condition requires that the investment increases strictly with productivity which requires all observations to

[5] Examples of shocks observable to the firm but not to the researcher are: management skills, defective product rates in a productive process, among others, while some examples of shocks that cannot be observed neither by firms nor by the researcher are: unexpected strikes, machines that fail unexpectedly, etc. (Ackerberg Caves and Frazer, 2015).

[7] For more detailed information, see Aguirregabiria (2009).

have strictly positive investment. This would reduce the sample size and thus estimation efficiency. Levinsohn and Petrin (2003) solve the endogeneity problem by using an intermediate input demand function to "invert" ω_{it} rather than using the investment demand equation as in Olley and Pakes (1996). Finally, Ackerberg, Caves and Frazer (2015), argue that the two previously described methods might suffer from a serious multicollinearity problem. In particular, in the first stage, labor may not vary independently of the polynomial used to approximate productivity. If this was the case, the labor coefficient would not be identified. This problem would be particularly serious if the inputs variable was used as a proxy variable (Ornaghi and Van Beveren, 2011). To solve this problem, they use the fact that labor is "less variable" than materials. For example, firms need time to train new workers, or to give workers a notice period before firing them (Ackerberg, Caves and Frazer, 2015). This implies that the demand for intermediate inputs becomes a function of capital, labor and productivity.[8] Importantly, while Olley and Pakes (1996) and Ackerberg, Caves and Frazer (2015) have focused on estimating value added models of production, Levinsohn and Petrin (2003) focus on a gross output specification, which, however, suffers from an identification problem (see Ackerberg, Caves and Frazer, 2015). Ghandi, Navarro and Rivers (2020) (GNR, henceforth) recently propose an estimation method which solves this identification problem non-parametrically, and, thus, makes the TFP estimation based on gross output operational. They illustrate the efficacy of their approach via Monte Carlo simulations and empirical applications with Colombian and Chilean Data.

In the next sections, we apply the GNR method using Chilean plant-level data from 1995-2007 to estimate productivity and decompose the TFP evolution by industry over the business cycle.

3 Data

We use the Annual National Industrial Survey (ENIA), which is a survey conducted on the Chilean manufacturing plants developed by the National Institute of Statistics (INE), covering plants with at least 10 workers. Plants keep their identification numbers only for the years 1995 to 2007, which allows us to form a panel only for this period. This survey includes employment by type; electricity and fuels consumption; costs of raw materials, intermediate supplies and services purchased; inventories and capital investments, sales and other sources of income, among others. For the different estimations we use the following variables: value of production, labor, capital, investment, raw materials and electricity. We work with real values, obtained by deflating the nominal variables by

[8] In addition to the methods mentioned above, there are alternative methods, including Arellano and Bond (1991), Blundell and Bond (1999) and Wooldridge (2009).

the proper price indexes whenever available (for different capital components, labor, etc) or converting to units of promotion (UF, a general and widely used Chilean price index).[9] Further, negative values of capital, investment, raw materials, added value or electricity are treated as measurement errors and consequently deleted.[10] We restrict our sample to plants with 15 (rather than 10) employees, in order to reduce spurious identifications of exit, insofar as plants disappear from the sample once they reduce their number of employees below 10. The data set consists then of an unbalanced panel with approximately 5,000 observations per year and 61,958 observations in total.

4 Estimation and analysis of TFP

In this section, we present the estimation of the production function obtained by the GNR estimation method. Table 1 shows the means and standard deviations of the estimated capital and labor coefficients for the different sectors.

Table 1: Estimation of the Production function

	Capital	Labor
Mean	0.144	0.396
Standard deviation	0.0828	0.150

Estimates of the production function (2) by GNR. Means of the estimated coefficients and their standard deviation.

The estimated coefficients vary between the sectors. The estimated contribution of capital to the value of production is on average 14.4% and the contribution of labor is on average 39.6%. Finally, the means of our estimates are comparable to the estimates in other papers using this data set for different time periods, such as Bergoeing and Repetto (2006).

Table 2 shows the moments of the estimated TFP (in logarithms) by plant size (panel a) and by industry (panel b). Smaller plants (in terms of number of employees) have the lowest productivity over the considered period and larger plants are more productive than smaller ones, which is in line with the theoretical prediction (see Jovanovic, 1982, Hopenhayn, 1982, Ericson and Pakes, 1995). In particular, larger plants are by 16% more productive than smaller and by 12% more productive than medium sized plants. The kurtosis is in all three cases above three, indicating heavy tails, but in the case of large plants less so, reflecting that the data are more concentrated around the average than in

[9] Following Greenstreet (2007), Bergoeing and Repetto (2006), and Bergoeing, Hernando and Repetto (2010), and Bergoeing, Hernando and Repetto (2006).
[10] Following Bergoeing, Hernando and Repetto (2006).

the case of small and medium plants. Further, medium and large firms, the distributions are positively skewed, while for small firms they are slightly negatively skewed. Table 2 (panel b) shows the moments of the TFP distribution by industry: the beverages and the other types of transport equipment are the most productive industry, followed by the common metals industry. Further, the beverage industry has the highest standard deviation but a rather small (positive) kurtosis, thus, it has very thin tails. Most other industries have heavy tails and all but the beverage industry are negatively skewed.

Table 2: Moments of the distribution of TFP

a) by plant size	N	Mean	Std. Dev.	Asymmetry	Kurtosis
Small	39,472	6.512	2.735	-0.0324	4.560
Medium	15,708	6.765	2.882	0.362	4.040
Large	1807	7.602	2.675	0.235	3.898

b) by sector	N	Mean	Stand. Dev.	Asymmetry	Kurtosis
Food	15,464	8.297	0.189	-2.840	27.777
Textiles	2947	4.312	0.144	-1.270	6.3
Clothing	3144	6.502	0.194	-1.843	8.063
Leather	1756	3.062	0.084	-1.002	5.603
Wood except furniture	3709	7.646	0.203	-1.448	6.313
Furniture	2837	3.209	0.142	-1.285	7.76
Paper	1574	7.94	0.168	-0.745	3.797
Editing	2494	5.466	0.172	-0.376	3.432
Chemical substances	3284	3.911	0.278	-1.404	6.151
Rubber and Plastic	3699	8.537	0.17	-1.011	4.32
Other non-metallic mineral products	2644	7.862	0.385	-0.297	3.36
Common metals	1390	10.042	0.401	-0.129	4.698
Metal products	4346	4.817	0.143	-1.223	6.493
Machinery and equipment	3164	3.949	0.167	-1.000	5.774
Machinery and electrical appliances	985	1.995	0.196	-0.429	4.498
Radio, television and comm. equip.	99	-5.243	0.185	-0.451	3.064
Medical, optical and precision instr.	324	5.787	0.239	-1.249	5.261
Motor vehicles, and (semi)trailers	906	-1.081	0.158	-0.901	3.668
Other types of transport equipment	579	13.944	0.149	-0.757	3.814
Beverages	1642	14.385	0.593	0.309	3.479

Small, medium and large plants are defined as plants with less than 50, between 50 and 400 and more than 400 employees, respectively. Industries are defined at three digit level according to the ISIC code.

5 Productivity decomposition over the business cycle

In this section, we decompose the aggregate productivity growth into terms (1) related to net entry of plants and (2) related to growth in continuing plants. Our analysis corresponds to Asturias et al (2020) who follow Foster, Haltiwanger and Krizan (2001). While Asturias et al (2020) base their decomposition on the Solow residual; we argue that the productivity is better obtained by estimating the production function at the plant level by Ghandi, Navarro and Rivers (2020). First, define the productivity of industry *i* as

$$\log Z_{it} = \sum_{e \in E_{it}} \mathrm{s_{et}} \log z_{et}$$

where E_{it} is the set of all plants in industry *i* and period *t* and s_{et} denotes the share of plant e's gross output in industry and z_{et} its productivity. Next define the productivity change from t-1 to t as $\Delta\log Z_{it}$. Then, the productivity can be decomposed into changes due to entering/exiting plants and changes due to continuing plants:

$$\Delta\log Z_{it} = \Delta\log Z_{it}^{NE} + \Delta\log Z_{it}^{C}.$$

The net entry in turn can be further decomposed into:

$$\Delta\log Z_{it}^{NE} = \sum_{e \in N_{it}} s_{et}\left(logz_{et} - logZ_{i,t-1}\right) - \sum_{e \in X_{it}} s_{e,t-1}\left(logz_{e,t-1} - logZ_{i,t-1}\right), \qquad (3)$$

with the first term representing entering plants (N_{it} is the set of all entering plants) and the second term exiting plants (X_{it} is the set of all exiting plants). While the continuing plants can be decomposed into

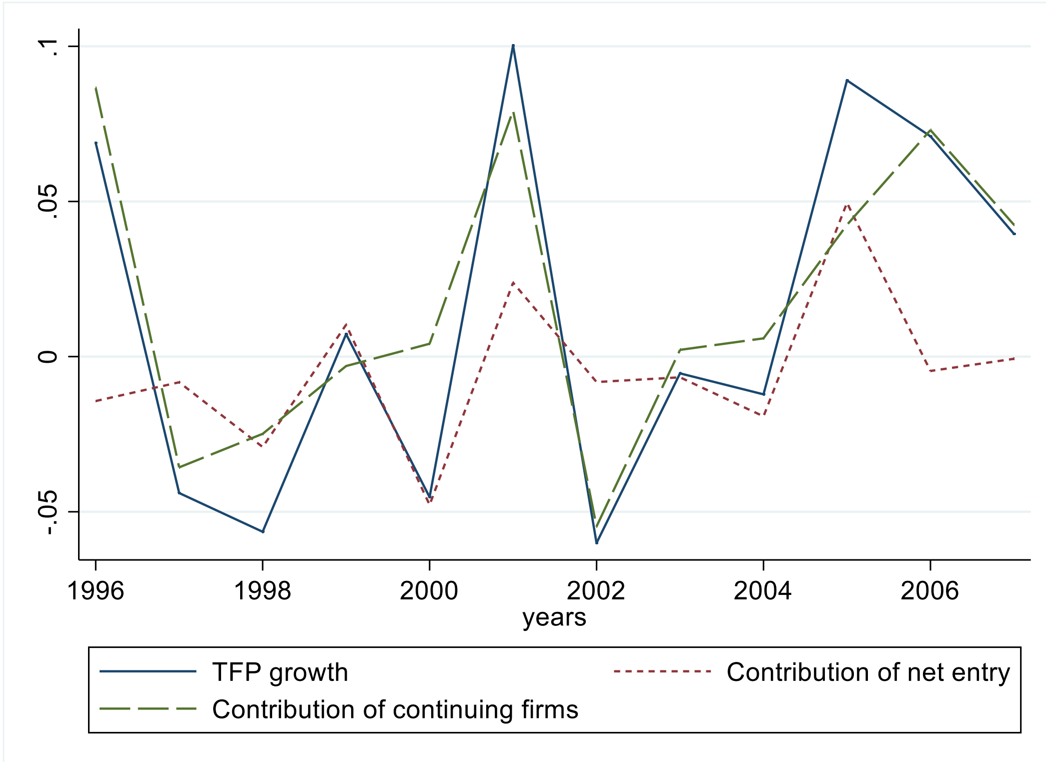
$$\Delta\log Z_{it}^{C} = \sum_{e \in C_{it}} s_{e,t-1} \Delta logz_{et} + \sum_{e \in C_{it}} \left(logz_{et} - logZ_{i,t-1}\right) \Delta s_{et}, \qquad (4)$$

with the first term denoting the contribution from within plant variation (average within-plant productivity growth) and the second reallocation (which is positive if relatively productive plants expand their market share), and where C_{it} is the set of all continuing plants.

Figure 1 decomposes the aggregate TFP growth into the contributions from continuing plants and net entry.[11] First, the contribution of net entry and continuing plants to TFP growth varies over the business cycle and even within the different expansion and recession periods. The declines in TFP during the Asian Crisis, 1997-1998, and during 2002-2004 comes, first, mainly from a negative contribution from continuing firms and, later on, mainly from a negative contribution from net entry..

Figure 1: Decomposition of TFP growth into net entry and continuing plants

[11] In order to limit the contribution of potential outliers, we limit the individual contributions to the aggregate TFP to 0.25%. This affects around 0.4% of the observations.



Yearly change in TFP and the contributions of net entry, equation (3), and of continuing plants, equation (4).

From Figure 1, the interval 1996 to 2007 can be divided into periods of high and low TFP growth and strong and weak TFP declines. Note that these TFP growth/decline periods are similar as expansions and recessions in terms of GDP, as discussed in the macro-literature specifically studying the business cycles of the Chilean economy[12] but do not completely coincide. For instance, Asturias et al (2020) classify periods as high growth differently than ours and also different from the ones in the literature. In particular, the recession periods, 1997-1999 and 2001-2003, behave quite differently in terms of their impact on TFP. During the first two years of the Asian Crisis, 1997-1998, TFP fell profoundly, while in the second period, TFP decreased sharply in 2002 and mildly in 2003-2004. Similarly, the growth periods differ, with the recovery year 2001, after the Asian Crisis and the dot-com bubble, showing the largest TFP increase, followed by the 2005-2006..

Table 3 decomposes TFP growth into its contributions from net entry and from continuing plants for the different years. The last column indicates the contribution of net entry to the TFP-growth.[14] Most

[12] Following Aldunate (2016), Agosin y Montecinos (2011), Cowan and De Gregorio (2007), Covarrubias (2001), Corbo and Tessada (2002), Schmidt-Hebbel (2006), and various reports of Central Bank of Chile on macroeconomic indicators.

[14] Note that if one of the two components grows while the other one shrinks, we set the growing one's contribution to 100% if overall TFP grows and to 0% if overall TFP shrinks.

remarkably, for the years with positive TFP growth, i.e. 1996, 1999, 2001, and 2005-2007, net entry contributes to the TFP growth mainly in the recovery year following a decrease: 1999, 2001 and 2005. The TFP declines in 1997-1998 and 2002-2004 start with a big negative contribution from continuing firms, while afterwards net entry plays a bigger role.

Table 3: Decomposition of TFP growth

Year	Annual TFP growth	Net entry	Continuing plants	contribution NE (in %)
1996	6.9	-1.4	8.7	0
1997	-4.4	-0.8	-3.6	18.8
1998	-5.6	-2.9	-2.5	51.6
1999	0.7	1	-0.3	100
2000	-4.5	-4.8	0.4	100
2001	10	2.4	7.9	23.8
2002	-6	-0.8	-5.5	13.6
2003	-0.5	-0.7	0.2	100
2004	-1.2	-1.9	0.6	100
2005	8.9	5	4.2	55.7
2006	7.1	-0.5	7.3	0
2007	4	-0.1	4.2	0

TFP growth and contribution to TFP evolution by continuing plants, equation (4), and net entry, equation (3).

Table 4 further decomposes the contribution of net entry into its contribution from exiting plants and entering plants, and the contribution of continuing plants into its contribution from within plants restructuring and reallocation. Both TFP growth and decrease due to continuing plants come mainly from within plants restructuring. For the contribution to net entry there is no clear pattern.

Table 4: Decomposition of contributions of net entry and continuing plants to TFP growth

year	Exiting	Entering	Contribution Exiting to NE	Within	Reallocation	Contribution Within to Continuing
1996	-0.9	-0.5	65.2	8.3	0.1	95.4
1997	1.3	-2.2	0	-3	-0.6	83.3
1998	-0.6	-2.4	19.3	-2.3	-0.2	92
1999	0.4	0.6	43.7	-0.6	0.3	100
2000	-0.9	-4	17.9	1	-0.6	100
2001	-0.5	2.9	0	8.8	-1.8	100
2002	-1.3	0.2	100	-5.4	-0.1	98.2
2003	-0.4	-0.6	62.5	0.5	-0.2	100
2004	1.3	-3.1	0	2.2	-1.7	100
2005	5.8	-0.9	100	5	-3.6	100
2006	0.1	-0.6	0	5	2.7	68.5
2007	0	-0.1	0	4.5	-3.6	100

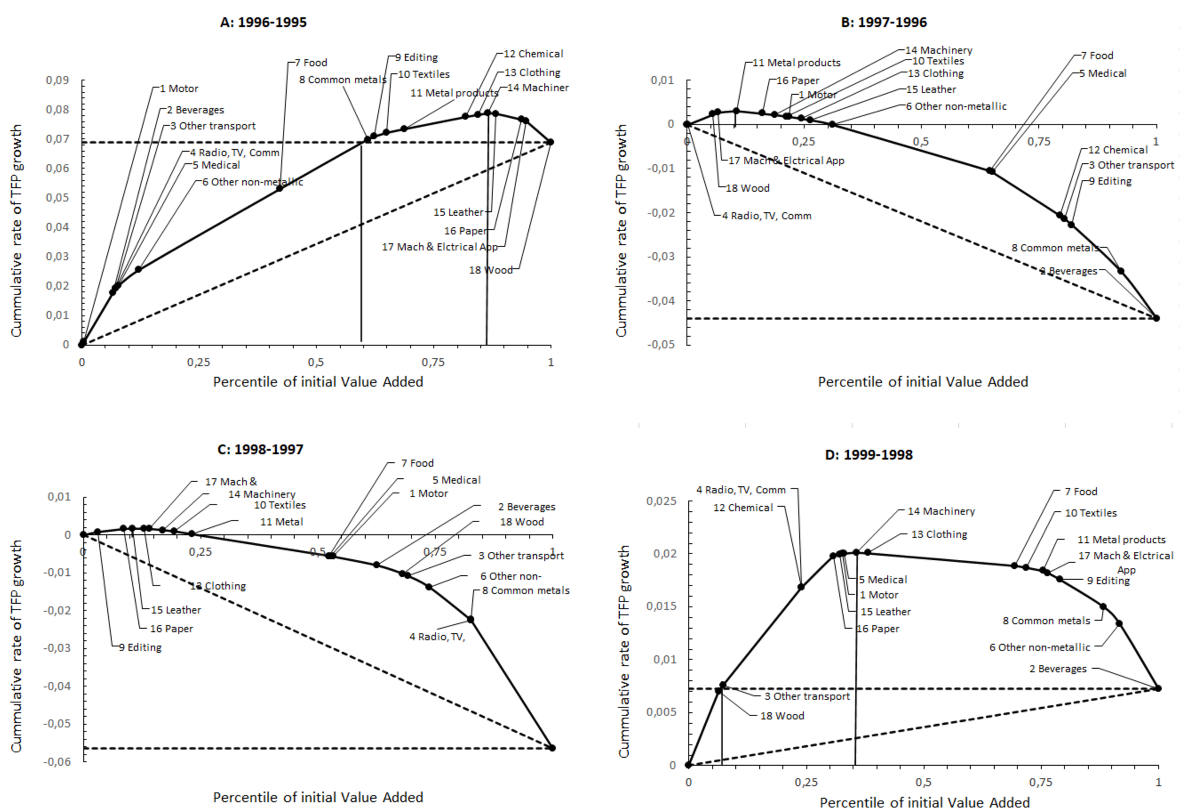
Comparing the previous findings with the ones in Asturias et al (2020) is difficult due to differences in the dataset (WHICH?), the employed method and the different classifications. In any case, our classification appears to be slightly more consistent with the classification of crises and booms in the Chilenean macro-literature. In any case, we find somehow similarly to Asturias et al (2020), that in the larger growth period the contribution of net entry is considerably larger than in low growth periods.

6 Industrial decomposition of the TFP evolution

As we have shown before, during the period 1996-1998, the Chilean economy suffered a persistent decline in TFP. In order to analyze this decline further, we implement the methodology developed by Harberger (1998) that allows us to analyze specific patterns of the importance and evolution of sectoral TFP. Harberger's diagrams, shown in Figure 2, complement our previous analysis by providing a graphical summary of the pattern of industrial productivity growth. In particular, they identify the relative importance of the different sectors over the business cycle.

They are constructed in the following way. First, for each year, industries are ranked according to their productivity growth rate in decreasing order. Then, the vertical axis depicts the industries' cumulative contribution to the aggregate TFP growth rate (measured by the growth rate of the product of the industry productivity change and industry initial share of value added), while the horizontal axis depicts the cumulative share of an industry's initial value added. In Harberger (1998), the vertical axis is called Real Cost Reduction rate (RCR) and is derived from the Solow residual as productivity measure. Here, we calculate the same variable but use a more advanced TFP estimate at plant and industry level via the Ghandi, Navarro and Rivers (2020) methodology (taking into account endogeneity, as explained before). In what follows we refer to it as the cumulative rate of TFP growth so as to closely follow Harberger's (1998) analysis of the productivity (RCR rate) patterns; yet with the same interpretation as before: the contribution of each sector to aggregate productivity growth.

Figure 2: Sunrise and sunset decomposition



The horizontal axis depicts the cumulative share of industry's initial value added of industries ranked according to TFP growth rate in decreasing order. The vertical axis depicts the cumulative contribution of the industries to the aggregate TFP growth rate (measured by the product of the industry productivity growth rate and the share of industry initial value added).

According to Harberger (1998), if all industries exhibited a uniform productivity growth (decline) the diagram would look like a monotonically increasing (decreasing) and concave function, showing a "yeast" configuration of growth (decline). In this case the growth pattern would be broad-based. Otherwise, if the relationship was non-monotonic, the pattern of growth would look like a "mushroom" configuration, in which only a limited number of industries concentrated the aggregate change in productivity. These diagrams exhibiting positive and negative growth are called sunrise and sunset, respectively.

From Figure 2, it is clear that TFP growth does not spread evenly across sectors, but is an unbalanced process following a mushroom pattern over time for all years considered. Here, we focus on the first GDP recession period 1996-1998 as well as the years right before and afterwards. Figure A1 in the appendix shows a similar growth pattern for the remaining years.

In particular, Figure 2, panel A, shows that in 1995-1996 the cumulative aggregate TFP of just 59 percent of the manufacturing industries (measured by initial value added, and indicated by the first vertical line) was equal to the total productivity growth for all sectors (aggregate change in TFP). [15] In addition, there are other industries with positive TFP growth representing around 27 percent of the total (indicated by the second vertical line) but their TFP growth contribution is compensated by yet another set of industries (14 percent of industries) with negative TFP change (the ones on the right of the second vertical line). This means that 86 percent of the industries, the winners, enjoyed a TFP increase (a real cost reduction) while the remaining industries, the losers, suffered from a TFP decline (real cost increase) reflecting the growth heterogeneity across sectors.

Regarding the recession, Figure 2 panel B, shows that, in the period 1996-1997, the cumulative net decline in productivity was concentrated in 69 percent of the manufacturing industries (measured by initial value added). There is one group of sectors composed of 11 percent of the industries (measured by initial value added) that enjoyed a TFP gain during this period. Another group of industries representing 20 percent of the total initial production suffered a decline in productivity and offset the positive contribution of the first group.[16] For the period 1997-1998, an even less concentrated group

[15] The following sectors concentrate the aggregate productivity growth: *motor vehicles, trailers and semi trailers; beverages; other types of transport equipment; radio, television and communications equipment and apparatus; medical, optical and precision instruments and watch manufacturing; other non-metallic minerals;* and *food.*

[16] The sectors that concentrated the aggregate productivity decrease are *food; medical, optical and precision instruments and watch manufacturing ; chemical substances and products; other types of transport equipment; editing; common metals;* and *beverages* (which is the main TFP loser).

formed by 77 percent of industries account for the whole productivity decline.[17] Six of the industries remained losers and seven of the industries remained leaders in both periods of TFP decline. From the remaining industries four industries changed from winners to losers, and one from loser to winner (in particular, editing changed from being the third largest loser to the largest winner).[18] This shows how unpredictable and volatile the TFP growth process is.

Finally, during the 1998-1999 period, interestingly with positive TFP growth, a highly concentrated group of just around 7.5 percent of the industries accounted for the whole positive change in TFP (see Figure 2, panel D). The contribution to TFP growth was concentrated in *wood except furnitures* and part of *other types of transport equipment*. Again, there is a dramatic change in the composition of the contributors to TFP growth with respect to the pre-crisis period.

Overall, the relative importance of the different sectors both in growth and decline periods considerably differs over time (for instance, during the period of TFP expansion in 1995-1996, *wood* is the main TFP loser, while in 1998-1999 it is the main TFP winner.

[17] Food; medical, optical and precision instruments and watch manufacturing; motor vehicles, trailers and semi trailers; beverages; wood except furniture; other types of transport equipment; other non-metallic minerals; common metals; radio, television and communications equipment and apparatus; and chemical substances and products dominated the TFP decrease.

[18] Radio, television and communications equipment and apparatus; wood except furniture; motor vehicles, trailers and semi trailers; other non-metallic minerals changed from winner to loser. Editing changed from loser to winner.

Table 5: Harberger´s diagrams features characterizing TFP growth patterns

Year	Annual TFP growth	Pervasiveness of Growth	Curvature	Excess growth volatility
1996	6.9	77.8	36.9	41.0
1997	-4.4	22.2	35.5	32.0
1998	-5.6	16.7	38.1	23.2
1999	0.7	50.0	77.0	92.5
2000	-4.5	55.6	56.3	80.0
2001	10	83.3	26.8	5.0
2002	-6	16.7	33.3	10.0
2003	-0.5	50.0	79.8	88.0
2004	-1.2	22.2	54.3	65.0
2005	8.9	77.8	49.3	60.0
2006	7.1	61.1	38.3	32.5
2007	4	50.0	44.1	50.0

In the second column, pervasiveness of growth is measured as the cumulative share of industries with a positive growth contribution. In the third column, curvature is measured by the area between the diagram and the diagonal line divided by the total area beneath the diagram (as in Inklaar ant Timmer, 2007). In the third column, excess growth volatility is measured as the fraction of industries (in initial value added terms) whose growth compensate each other, contributing zero to the aggregate net TFP change as a whole.

7 Conclusion

The previous literature on productivity dynamics is ambiguous in identifying the main components contributing to TFP changes over time, insofar as it finds net entry to play a minor role for the US economy, a significant role for China, and an important role in periods of high growth for Chile and Korea. We estimate TFP from Chilean plant level data by the method proposed by Ghandi, Navarro and Rivers (2020) taking into account simultaneity, and study the relative contribution of net entry and continuing firms and the sectoral concentration of changes in TFP over the whole business cycle (including recessions). We find that net entry contributes to TFP changes mainly in the growth periods directly following TFP declines. The TFP declines in 1997-1998 and 2002-2004 start with a big negative contribution from continuing firms, while afterwards net entry plays a bigger role.

Further, in line with Harberger (1998), few sectors are responsible for most of the TFP growth (decline) of aggregate productivity, and the remaining sectors, consisting of TFP winners and losers, offset each other's contribution to TFP changes. In addition, the relative importance of the different sectors to both growth and decline periods differ over time.

A potential extension could be to analyze patterns resulting from the decompositions by both Asturias et al (2020) and Harberger (1998) within each industry and period.

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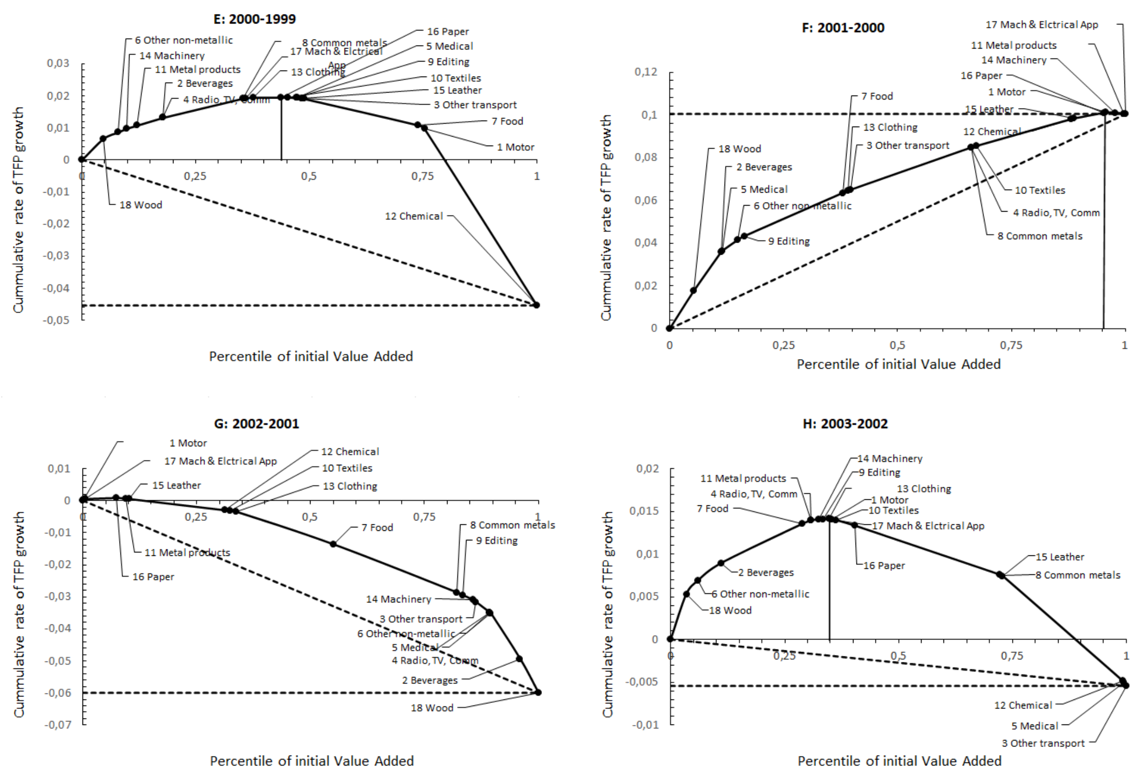
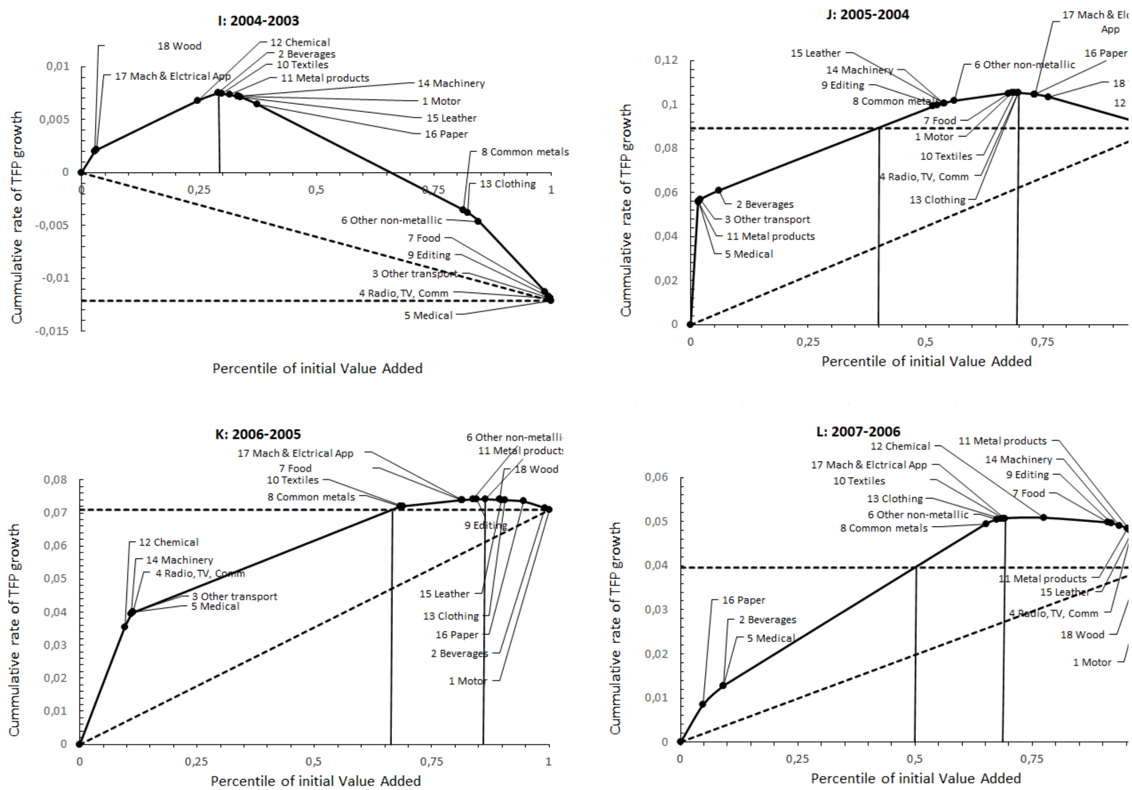
Appendix

Figure A1: Sunrise and sunset decomposition for 1999-2007





See description below Figure 2.