PRODUCTIVITY AND FIRM HETEROGENEITY IN CHILE

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Abstract

We analyze productivity growth in Chilean manufacturing 1979-2000 using the newly available panel of establishments drawn from the Census of Manufacturing. We examine the contribution to productivity growth of 'internal' restructuring (such as new technology and organizational change among survivors) and 'external' restructuring (exit, entry and market share change). We find that (a) 'external restructuring' accounts for 52% of industry labour productivity growth and 57% of industry TFP growth; (b) much of the external restructuring effect comes from the closing down of poorly-performing plants due to import penetration, and (c) import penetration is also an important determinant of internal restructuring in the long term.

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1 Introduction

Much of the traditional analysis on the sources of growth, both in industrialised and in developing countries, has been based on some kind of *Growth Accounting* exercise. Since Solow (1957), the mainstream approach has always been to try to explain aggregate output growth using weighted growth of (sometimes quality-adjusted) production inputs and a residual.[2] Since the earliest applications of this methodology, one of the most astonishing results is how small the growth in the inputs is in relation to the growth of the output, and how important is the residual in explaining the aggregate growth process. Following Harberger (1998), two explanations have been put forward for the relative magnitude of the residual: input measurements errors and technical change. As a consequence, the original growth accounting methodology has been expanded with the introduction of several corrections for differences in the quality of the production inputs, in particular human capital (for instance, Jorgenson and Griliches, 1967). These sorts of corrections typically generated a reduction in the importance of the residual as a source of growth, but never completely eliminated its influence. Because of this, over time, the idea of the residual (and total factor productivity – TFP) became ever more closely allied to the concepts of technical change, production efficiency and innovation. The estimates of the residual obtained with the growth accounting framework were then used as the basis for policy discussions about human capital formation, research and development, trade, infrastructure, privatisation, etc.

Despite all these modifications and improvements, we consider that the main problem with the traditional growth accounting methodology is that it is based, either explicitly or implicitly, on a model in which identical, perfectly competitive plants all respond in the same way to forces that affect industry as a whole. Because of this, the method is (at best) only capable of producing a measurement of multifactor productivity but not explaining it[3]. It conflicts with the literature on industrial evolution (see, for example, Audretsch, 1995 and Klepper, 1996) which shows that the innovation process is the consequence of the investment decisions taken by firms, whose uncertain results lead some of them to grow, others to decline, and many to be replaced by better start-ups.

[2] See Harberger (1998) for a detailed summary of the methodology of growth accounting and the explanation of the residual.
[3] Or, what is worse, sometimes misinterpreting it as a kind of technical progress or cost reduction widely available to all the agents in the economy.

Since Baily, Hulten and Campbell (1992), interest in clarifying our understanding of the residual, improving the economics of productivity analysis, and reconciling it with the industrial evolution models, has been increasing. The main driving force of this research is the claim that a model of aggregate economic growth and productivity increase must be consistent with the wide diversity of plant-level performance that is observed in the micro-data.

In the spirit of this new research agenda, we apply in this paper an *alternative* growth accounting methodology. Instead of working at aggregate level we focus on the micro-foundations that underlie the functioning of capitalist economies: *the competition process*. That is, in our methodology TFP (the residual) at aggregate level must be constructed from the residuals of thousands of different plants, each weighted by its corresponding market share. Within this framework we explore the heterogeneity among plants and see how individual plants move across the TFP distribution, which plants account for most of the aggregate productivity growth, and how important entry and exit are to industry productivity growth.

We implement our approach Chilean manufacturing micro-data. We believe that there are several reasons why the Chilean manufacturing is worthy of study. First, as Liu (1993) points, Chile is among the most successful examples of a fast-growth developing country. Second, it is usually assumed that as a consequence of its previous structural reforms, the Chilean economy, and in particular manufacturing, suffers from very few distortions, thus allowing for more reliable TFP estimations. Finally, the micro-economic regime has remained the same for the last 25 years, leading to a context of stability in the incentive system. This is a feature that is quite remarkable in a developing country context,[4] and makes the identification of the long run trends of growth much easier..

Having a framework for TFP measurement grounded in micro-data is also critical to obtain a better understanding of the impacts of major policy changes and exogenous shocks. In many cases the impact of these structural reforms and other exogenous shocks, has been evaluated by focusing on the induced changes in performance of some representative (typically average) plant. Therefore, it has been typically assumed that plant-level responses (costs and benefits) to a given policy change or shock are uniform for all the plants in the industry. This sort of analysis clearly produces some inconsistent results.

Let us look at the case of trade liberalisation. In the standard representative plant approach it is usually found that trade liberalisation increases plant productivity (see, for example, Agacino, Rivas and Roman, 1993; Alvarez and Fuentes, 1999; Aw, Chen and Roberts, 2001; and Tybout, 1996). But, if this is an outcome that is uniformly shared by all the plants, why are governments suddenly so reluctant to implement these sorts of policies? The reason becomes clearer if we instead believe that the responses to policy changes are heterogeneous and that while some plants adapt and react favourably to the new incentive framework, many others fail and exit the market. If this is considered to be important, the social-political costs of certain policy changes will increase considerably, and their implementation might call for certain complementary interventions.

The current research is not about policy impacts, but the foregoing paragraphs must be taken as examples of the need to generate a productivity accounting framework, which, based on micro-data, is able to identify the main sources of aggregate productivity growth. In the face of this complexity, we proceed with a minimum amount of structure. Our proposition is hence to use Chilean micro-data to contrast alternative views about the appropriate model for explaining the distribution of TFP across plants and its evolution over time. The paper is divided into the following sections. Section 2 presents the data set, its coverage and sampling. Section 3 develops the methodology used to measured plant level total factor productivity. Section 4 summarises the different approaches used to decompose aggregate productivity growth. Section 5 presents the findings concerning the measurement of total factor productivity (TFP) and the sources of aggregate productivity growth. Section 6 makes a first effort to link the changes in TFP to the process of trade liberalisation. Section 7 summarises the stylised facts and the main conclusions.

[4] Even though the economy suffered at least two adverse (external) macroeconomic shocks during the last 25 years.

2 The Data Set: Description, Coverage and Reliability

This paper applies index number techniques to construct plant-specific time-variant productivity indices. These indices are then used to compare productivity growth rates across plants. The analysis is based on plant-level panel data from Chile covering the period 1979-2000: the *Encuesta Nacional Industrial Annual* (the Annual National Manufacturing Survey, ENIA) collected by the *Instituto Nacional de Estadisticas* (INE). It should be noted that the first part of this panel database, corresponding to the period 1979-1986, has become something of a *public user database*, and has been previously used by several authors. However, extension of the time period covered and the inclusion of additional variables is unique to this research. The database includes all Chilean manufacturing plants with at least ten workers that have been active in the Chilean manufacturing sector between 1979 and 2000. This is a long time span, which allows us to identify the properties of the learning underlying the productive units' capabilities accumulation, and also the consequences of the selection processes at sector level.

There are 100,141 observations in the data set5 and, as we can see from Table 2.1, roughly 30% of them are in the foodstuffs sector, between 15% and 20% in textiles and metalworking and 10% in wood and furniture, and chemicals. These sector shares are stable over time; however it is possible to identify some interesting trends. Over the whole period the textile-related manufacturing branches lose about 7 percentage points in terms of productive units, losses that are offset by an increase in the shares of metalworking and, more marginally, chemicals. However, broadly speaking, there are no dramatic changes in the manufacturing structure in terms of sector shares (what is termed "structural change"). It is important to emphasise here that the sample is focused on the time period "after" the most important pro-market reforms and hence it is expected that in our sample we have relatively stable shares of the different manufacturing branches.

[5] Actually, there are 105,202 observations in the original dataset, however some partial cleaning of it was required before processing. Some records could not be used because of highly incomplete data about key variables such as employment, production, value added and even "extra-manufacturing" sector classifications. There is no clear pattern across sectors or sizes for these missing records, and we think they are likely due to administrative errors on the part of the unit in charge of collecting the survey.

Table 2.1

Number of Manufacturing Plants by Sector (2-Digit Level) and Year

	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Foodstuff	1805	1678	1566	1520	1491	1516	1502	1438	1476	1478	1471	1486	1503	1540	1520	1502	1483	1600	1563	1492	1385	1373
	32	33	34	35	37	36	37	36	34	35	34	34	33	33	32	31	30	31	31	33	33	32
Textile & Apparel	1167	1036	920	808	741	777	752	758	845	819	813	834	876	905	853	868	841	906	820	697	639	623
	21	20	20	19	18	19	18	19	20	19	19	19	19	19	18	18	17	17	16	15	15	14
Wood & Furniture	706	616	553	476	429	433	433	396	410	395	415	418	417	432	510	506	504	550	525	470	418	413
	13	12	12	11	11	10	11	10	9	9	10	10	9	9	11	10	10	11	11	10	10	10
Pulp, Paper & Printing	295	280	251	236	214	210	205	203	240	235	234	237	250	260	274	278	272	284	275	256	249	284
	5	6	5	6	5	5	5	5	6	6	5	5	6	6	6	6	6	5	6	6	6	7
Chemicals	427	410	382	359	346	384	378	378	417	414	428	437	473	500	538	551	577	573	548	514	471	500
	8	8	8	8	9	9	9	9	10	10	10	10	10	11	11	11	12	11	11	11	11	12
Non Ferrous Minerals	165	166	153	135	122	126	132	126	133	125	129	140	157	167	170	186	187	198	191	169	165	160
	3	3	3	3	3	3	3	3	3	3	3	3	3	4	4	4	4	4	4	4	4	4
Basic Metals	91	75	66	60	55	55	55	55	72	87	70	68	67	65	69	67	75	83	75	72	60	92
	2	1	1	1	1	1	1	1	2	2	2	2	1	1	1	1	2	2	2	2	1	2
Metalworking	831	760	708	637	575	615	609	599	681	651	691	682	727	767	811	824	898	945	925	846	740	833
	15	15	15	15	14	15	15	15	16	15	16	16	16	16	17	17	18	18	19	19	18	19
Other	73	61	58	51	41	45	47	45	53	46	49	50	50	51	54	59	64	96	64	56	49	50
	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1
Total	5560	5082	4657	4282	4014	4161	4113	3998	4327	4250	4300	4352	4520	4687	4799	4841	4901	5235	4986	4572	4176	4328
	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Note: alternate rows show the column %. Source: Instituto Nacional de Estadistica.

The time pattern of missing values for each plant can be used to identify entering, exiting and surviving plants. Surviving plants ("survivors") remain in the sample for the entire 1979-2000 time period, so there is no change in their sample size. The rest of the plants can be divided into three broad categories: entrants - plants that are present in 2000, but not in 1979; exits - plants that show up in 1979, but not in 2000; and finally plants that are in the database, but do not show up in either 1979 or 2000, which we call temporary plants.

Table 2.2
Proportion of Plants, Output and Employment by plant category

Status	Plants	Output	Labour
Survivor	0.31	0.50	0.42
Entrant	0.19	0.21	0.16
Exit	0.34	0.18	0.29
Temporary	0.17	0.10	0.13

Note: Rows represent shares in total manufacturing.

The survivor plants represent 31% of the total sample (see Table 2.2), the entrants almost 20%, the exits about 34%, while the remaining 17% corresponds to temporary plants. There are interesting differences in terms of output shares. The survivor plants account for 50% of production, while the exit plants represent only 18%. This remarkable contrast between the shares of plants and output in the case of the exit plants clearly suggests that these plants are of below average size. However, when we look at the output shares of the entrants we see that they are almost in proportion, allowing us to infer that new and larger entrants usually replace exit plants. Another group where it is possible to see some asymmetric distribution between observations and output is the temporary plant group, suggesting again that it is the very small plants that most often move in and out of production. Similar observations can be made about employment. In addition, by comparing output and employment shares, it can be seen that the survivor plants and entrants have larger than average labour productivity, while the opposite is true for the exit and temporary plants[6]. In the Appendix we also present a reliability

[6] One important qualification should be made regarding this overview of plant turnover. A particularity of the manufacturing census is that although many plants enter or exit the database, defining them as greenfield entrants and closed-down exits is not strictly appropriate in most cases. The majority of the entering and exiting plants appear or disappear on the basis of the 10 employees threshold, and the INE does not include specific reasons for why plants enter or exit the database. However, although many of the plants enter or exit the database on the basis of reaching or not the observation threshold, we will still label them as entrants and exits. Certainly, any empirical test aiming to identify the determinants of entry and exit decisions, would be very imprecise. But, as Van Dijk

analysis regarding the ENIA's sample coverage and statistical representation. In what follows we describe the procedures used in order to compute plant-level TFP and on the various methodologies that we applied to obtain our productivity decompositions.

3 Total Factor Productivity Measurement: the Index Number Methods[7]

Our goal is to construct an index of plant-level TFP for each plant in each year of the sample. Index number approaches applied to measuring productivity have the advantage of not requiring direct estimation of the underlying technology, and therefore of not demanding the specification of some econometric model which would raise the identification problems pointed out in Griliches and Mairesse (1998). The cost of all of this is that the results are more sensitive to measurement errors in the variables. Index number approaches provide the most flexible framework for productivity measurement by simply exploiting the basic idea that a TFP index measures the ratio of outputs to inputs usage. In this paper we calculate (log) TFP as

$$tfp_{jt} = y_{jt} - \sum_{i=1}^{n} \alpha_i x_{ijt} \quad (3.1)$$

where y_{jt} is (log) gross output by plant j at time t, x_{ijt} is (log) input i for plant j at time t, the α's are the output shares of each production factor,[8] and tfp_{jt} is the (log) productivity index. The factor shares are calculated at the three-digit industry level averaged over the beginning and ending year of the sample time period. As before, in order to ensure that the productivity index has the desired properties, such as transitivity and insensitivity to the units of measurement, it is necessary to normalise (3.1) by same reference plant. In this case we carried out the normalisation by simply subtracting the productivity of a reference plant in a base year (a plant with mean output and mean input levels in 1979

(2001) points out, for cross-sectional industry comparisons the database can still be useful for studying these processes if we make the assumption that it is easier for small plants to grow and pass the observation threshold in sectors where greenfield entry is also easier.

[7] For a comprehensive treatment of this topic see Good, Nadiri and Sickles (1996) and Coelli et al. (1998).

[8] Cost shares instead of output shares were also considered. Results were relatively robust to this alternative specification.

in the corresponding 3-digit ISIC sector) from an individual plant's productivity measure:

$$tfp_{jt} = y_{jt} - \sum_{i=1}^{n} \alpha_i x_{ijt} - \left(\bar{y}_{t0} - \sum_{i=1}^{n} \alpha_i \bar{x}_{it0} \right) \quad (3.2)$$

where the bar over a variable indicates the long (mean) over all plants in a base year, in this case 1979. This productivity measure represents a logarithmic deviation of the plant's peformance from the mean industry practice in the base year. Although a multilateral chained index has better theoretical properties than the one that we use here, it is rarely used in empirical work (one notable exception is Aw *et al.* (2001) in their study of productivity in Taiwanese manufacturing). Other studies, such as Baily *et al.* (1992) for the US, Olley and Pakes (1996) for the US telecommunication equipment industry, Haltiwagner (1997) and Foster *et al.* (2001) also for the US, Hugget and Ospina (2001) for Colombia, Pavcnik (1999) for Chile, Disney *et al.* (2003) for the UK, Masso, Eamets and Philips (2004) for Estonia and Barnes *et al.* (2001) for a sample of OECD countries, use the more standard Solow index of productivity given by (3.1).

Three inputs are, partially, observed in the dataset: employment, raw materials and capital stock. In order to measure the input shares we need information about input current costs. We have information for the current costs of all inputs except capital services, hence some assumptions needs to be made to calculate the input shares. Following Hugget and Ospina (2001) we construct a common nominal price of capital services for each year so that, at this price, the nominal value of gross production for all manufacturing equals the nominal value of all input costs. This amounts to assuming the there are no *aggregate* profits for the *entire* manufacturing sector in every year. However, at plant level it is perfectly possible that some of them experience profits while others have losses. One important advantage of this methodology is that we estimate factor elasticities that do not add to unity, this avoiding the assumption of constant returns to scale.

4 Total Factor Productivity Decompositions[9]

Since the pioneering work of Baily *et al.* (1992) several, more complementary than alternative, methodologies for productivity decomposition have been suggested. Broadly speaking, what all of them try to do is to disentangle the microeconomic foundations of aggregate productivity growth; that is, they answer the research question of to what extent is aggregate productivity growth the result of plant (or firm) level improvements (consequences of learning-by-doing or re-tooling processes) or resource reallocations not only across firms (or selection), but also across sectors (that is, structural change).

The original methodology formulated by Baily *et al.* (1992) (hereafter BHC) starts from the recognition that the index of industry-level productivity in year t is given by:

$$tfp_t = \sum_i \theta_{it} tfp_{it} \qquad (4.1)$$

where θ_{it} is the market share (in terms of gross output or employment) of plant i in period t for the respective industry. Industry productivity growth between periods t and $t\text{-}k$ is measured as:

$$\Delta tfp_t = tfp_t - tfp_{t-k} \qquad (4.2)$$

We can proceed now by defining the productivity in t and $t\text{-}k$ as:

$$tfp_t = \sum_S \theta_{it} tfp_{it} + \sum_N \theta_{it} tfp_{it} \quad (4.2')$$

and

$$tfp_{t-k} = \sum_S \theta_{i-k} tfp_{it-k} + \sum_X \theta_{it-k} tfp_{it-k} \quad (4.2'')$$

where S means that the sum is over the survivor plants, N identifies the entrants and X refers to the exits. By substituting both (4.2′) and (4.2″) into (4.2) we can write:

[9] For a comprehensive treatment of this topic see Foster et al. (2001).

$$\Delta tfp_t = \sum_S \theta_{it} tfp_{it} - \sum_S \theta_{it-k} tfp_{it-k} + \sum_N \theta_{it} tfp_{it} - \sum_X \theta_{it-k} tfp_{it-k} \quad (4.3)$$

Equation (4.3) can be re-arranged by adding and subtracting to right-hand side the plant-level productivity in year *t* for the survivor plants weighted by the market shares in year *t-k.* As a consequence of this transformation we can re-write equation (4.3) as follows:

$$\Delta tfp_t = \sum_S \theta_{it-k} \Delta tfp_{it} + \sum_S tfp_{it} \Delta\theta_{it} + \sum_N \theta_{it} tfp_{it} - \sum_X \theta_{it-k} tfp_{it-k} \ (4.4)$$

where $\Delta tfp_{it} = (tfp_{it} - tfp_{it-k})$ and $\Delta\theta_{it} = (\theta_{it} - \theta_{it-k})$. Equation (4.4) has four terms, each capturing a different source of aggregate productivity growth. The first term on the right hand-side measures the plant level improvements made by the incumbents or survivor plants (and is related to learning-by-doing, innovation and re-tooling processes developed within survivor plants). The last three terms capture the influence of selection, which is composed of the market share reallocations among incumbents and the replacement effects from new entrants replacing exit plants. In the words of Disney *et al.* (2003), while the first term on the right hand-side measures "internal restructuring" the last three terms identify "external restructuring".

Haltiwagner (1997) points out that a problem with the BHC decomposition is that even if all plants have the same productivity in period *t* and *t-k*, the formula (4.4) might yield a non-zero between-plant term and an offsetting non-zero net entry term if the share of output due to entering plants is different from the share of output due to exiting plants. Indeed, if the market share of entrants is smaller (larger) than the market share of exiters, we would have a bias towards a positive (negative) between-plant term and a negative (positive) net entry term. In order to overcome this problem Haltiwagner (1997) recommends "normalising" the productivity of each plant regarding the weighted average productivity of the industry in the base year. That is, we start from an expression such as:

$$tfp_t = \sum_i \theta_{it} (tfp_{it} - tfp_{t-k}) \qquad (4.5)$$

where tfp_{t-k} is the weighted average productivity of the industry in year *t-k*. Departing from (4.5) a series of transformations are developed in order to obtain the following alternative decomposition (termed FHK here[10]).

$$\Delta tfp_t = \sum_S \theta_{it-1}\Delta tfp_{it} + \sum_S \Delta\theta_{it}\left(tfp_{it-k} - tfp_{t-k}\right) + \sum_S \Delta\theta_{it}\Delta tfp_{it} + \\ + \sum_N \theta_{it}\left(tfp_{it} - tfp_{t-k}\right) - \sum_X \theta_{it-k}\left(tfp_{t-k} - tfp_{t-k}\right) \qquad (4.6)$$

In the FHK decomposition, the first term represents a within-plant component based on plant level changes, weighted by the initial shares in the industry. The second term represents a between-plant component that reflects changing shares, weighted by the deviation of initial plant productivity from the initial industry index. The third term represents a covariance type term that captures the co-movements between plant productivity growth and changing market shares. The last two terms represent the contribution of entering and exiting plants, respectively.

In this decomposition, the between-plant term and the entry and exit terms involve deviations of plant-level productivity from the initial industry index. For a survivor plant, this implies that an increase in its share contributes positively to the between-plant component only if the plant has higher productivity than the initial industry average. Similarly, an exiting plant contributes positively only if the plant exhibits productivity lower than the initial average, and an entering plant contributes positively only if the plant has higher productivity than the initial average.

Although the FHK method produces more meaningful decompositions, Foster *et al.* (2001) report that their method is very sensitive to errors of measurement in the variables. Following their example, if output is used as a weight for TFP and there is a classical random error in the same variable in *t-k*, this will yield a positive covariance between productivity changes and share changes and a spuriously low within-plant effect. In cases where one suspects the errors of measurement are important Foster *et al.* (2001) also recommend the decomposition formulated by Griliches and Regev (1995).

[10] We use the term FHK decomposition following the nomenclature in Disney et al. (2003), because Foster et al. (2001) popularised the application of this method.

Griliches and Regev (1995) propose that the productivity of each plant should be written as deviations of the average productivity of the industry *over time*. That is, if we are considering two periods, *t* and *t-k*, the starting point will be established by :

$$tfp_t = \sum_i \theta_{it}\left(tfp_{it} - tfp\right) \quad (4.7)$$

where tfp is the mean of industry weighted average productivity between *t* and *t-k*. After rearranging terms, the Griliches and Regev (GR) productivity decomposition will be given by:

$$\begin{aligned}\Delta tfp_t = {} & \sum_S \theta_i \Delta tfp_{it} + \sum_S \Delta\theta_{it}\left(tfp_i - tfp\right) + \sum_N \theta_{it}\left(tfp_{it} - tfp\right) \\ & - \sum_X \theta_{it-k}\left(tfp_{t-k} - tfp\right)\end{aligned} \quad (4.8)$$

where the lack of a time subscript means that the variable is an average of the variable over the base and end years. The first term is the within-effect that is measured as the weighted sum of productivity, with the weights equal to the average shares of the survivor plants. The second term is a between-effect, where the changes in the shares are weighted by the deviations of average plant-level productivity from the industry grand mean. This implies that this between term will be positive if plants that over the whole period have higher-than-average productivity, gain market share. In the same way, the net entry terms are such that entry contributes positively as long as entering (exiting) plants have a higher productivity than the overall average. This method is expected to be less sensitive to measurement errors because it uses averages that cancel them out. However, as Disney *et al.* (2003) point out, the disadvantage of the method is that in the decomposition the within-effect will reflect part of the selection effect since this affects the market shares at the end of the period. In the existing empirical work several variations of the above decompositions have been produced (see for example Levinsohn and Petrin (1999) and Aw *et al.* (2001)).

A final suggested decomposition is the cross-sectional methodology utilised by Olley and Pakes (1996). The method considers that in every time *t* the productivity of the industry can be defined as:

$$tfp_t = \overline{tfp}_t + \sum\left(\theta_{it} - \overline{\theta_t}\right)\left(tfp_{it} - \overline{tfp}_t\right) \quad (4.9)$$

where a bar over a variable represents the cross-sectional mean across all plants in the same industry. The second term in this decomposition provides an indication of whether the resource reallocation process is enhancing industry-wide productivity. As Foster *et al.* (2001) point out this method is the most robust to measurement errors in the variables. However, it does not allow characterisation of the role of entry and exit and it will not be applied here.

5 Total Factor Productivity Estimates: Stylised facts for the Chilean manufacturing sector

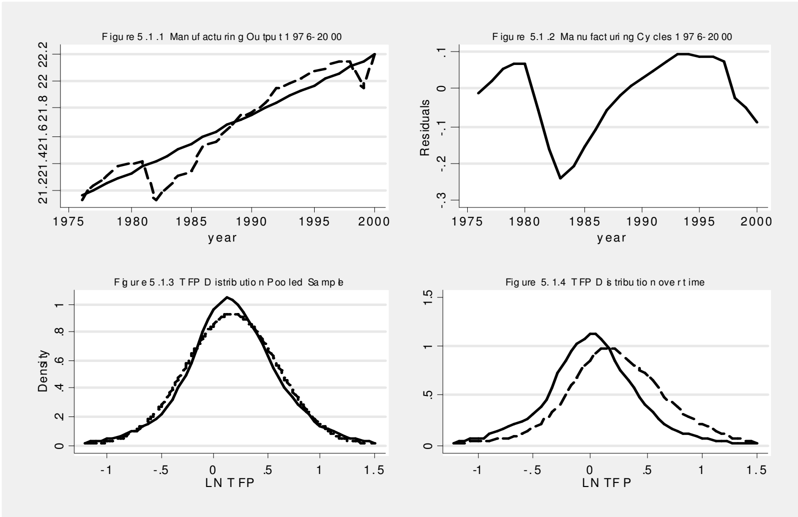
5.1 Aggregate Trends in Chilean Manufacturing

The data set covers the period following the reforms of the mid-1970s in the Chilean economy, a period over which it is possible to clearly identify one fully observed business cycle in terms of the evolution of manufacturing output. This fact is evident from the top panels of Figure 5.1, which show respectively, the long-run trend of manufacturing output and its cycles. It can be inferred from them that at the beginning of the period the economy (and also manufacturing) was recovering from the huge contraction shocks produced by the stabilisation programme of the mid-1970s. This upward phase reached a peak in 1980 and then the economy went into a deep recession as a result the debt crisis at the beginning of the 1980s. Manufacturing output shrank until 1983 and then, as the international context improved and the incentives from the new macroeconomic regime took effect, recovered very quickly, reaching a new peak in 1993. After 1993, manufacturing output growth slowed, first as a consequence of the strong peso of the mid-1990s and second as a response to the effects of the Asian Crisis in 1997.[11] The economy was in recession by 1999, although it had started to recover in

[11] The Asian countries are among the largest export markets for Chilean raw materials and basic manufacturing products.

2000. Thus, it can be seen that the time period 1979-1993 covers a full business cycle. Therefore, we focus on this period for many of the analyses described in this paper.

Figure 5.1. Trend and Cycles in Chilean Manufacturing



This section also characterises some features of the distribution of the TFP index, not only at an aggregate level, but also in each of the individual sectors. In order to extrapolate the plant measures to the corresponding level of aggregation, the individual measures have been weighted by the share of the employment of each plant in total employment. The results of this exercise can be seen in the bottom panels of Figure 5.1.[12] In the right hand bottom panel, we compare the TFP empirical distribution for the whole of manufacturing between the years 1979 and 2000 (the beginning and the end of the sample period). From the figure we can infer that over this period as a whole:

(i) The centre of the distribution changes. Compared with the 1979 the empirical distribution for 2000 is always moved towards the right, capturing the effects of systemic productivity growth over the period.

(ii) The TFP index for the vast majority of plants is located in the interval between -150% and +150%, indicating a massive degree of heterogeneity.

(iii) A small percentage of plants have relative productivity indices greater than +100% or smaller than -100% and the (log) TFP distributions look relatively symmetric.

[12] The distributions have been trimmed at the lowest and upper 1% in order to control for the influence of outliers.

In order to obtain a better idea about the general trends over this period, Table 5.1 shows the corresponding growth rates. Manufacturing output grew over the period 1979-2000 at a rate of 4.0% per year. However, there are very large fluctuations over the different phases of the business cycle: manufacturing output declined 4.0% per year during the contraction at the beginning of the 1980s and, after the crisis, it recovered at 7.7% per year, reaching a new peak in 1993. Since that time manufacturing growth rates have been much more modest (a little less than 3.2%). The second column shows the growth rate between what are roughly the two peaks, which suggests that the long-run manufacturing growth rate was 4.4%. The second row of the table shows employment growth. One thing that is clear from the tables is that, while employment strongly declined during the contraction phases of the business cycle, it did not recover at the same pace as output during the expansions. As a consequence, we observe positive labour productivity growth in almost every sub-period. Indeed, long-run labour productivity growth was about 2.2% between 1979 and 1993, with the also quite remarkable finding of positive labour productivity growth even during the contraction periods of 1979-1983 (2%) and 1993-2000 (7.6%).

Table 5.1
Summary Statistics (% per year)

	1979 to 2000	1979 to 1993	1979 to 1983	1983 to 1993	1993 to 2000
$\Delta \ln Y_t$	4.0%	4.4%	-4.0%	7.7%	3.2%
$\Delta \ln L_t$	0.0%	2.2%	-8.5%	5.7%	-4.4%
$\Delta \ln M_t$	4.8%	5.2%	-2.7%	8.6%	3.8%
$\Delta \ln K_t$	1.4%	-0.5%	-6.2%	0.9%	5.3%
$\Delta \ln (Y_t/L_t)$	4.0%	2.2%	4.5%	2.1%	7.6%
$\Delta \ln TFP_{st}$	0.8%	1.2%	0.5%	1.7%	0.1%

Note: All numbers are average annual percentage growth weighted by employment-population. The years are chosen to correspond with troughs and peaks according to Figure 5.1. $\Delta \ln (Y_t/L_t)$ and $\Delta \ln$ TFP are calculated by computing for each establishment $\ln (Y_t/L_t)$ and ln TFP and weighting by employment. The calculations therefore include entrants, exits and survivors.

Regarding the other two inputs, while raw materials and other intermediate inputs closely follow the evolution of manufacturing output, there are considerable differences in the performance of capital services. Over the whole period capital services grew at 1.4% per year, but this is mostly explained by very significant growth during the last sub-period. Indeed, capital services declined first by 6.2% per year during 1979-1983 and increased 0.9% per year in the sub-period 1983-1993, but increased at a dramatic pace during the late 1990s when they grew by 5.3% per year.

The last two row of Table 5.1 focuses on TFP results. TFP growth was 0.8% for the whole period. The long-run TFP growth rate was 1.2%. In relation to international comparisons, these figures appear lower (higher) than those for the UK, where Disney *et al.* (2003) find annual equivalent growth rates of 4.5% for labour and 1.06% for TFP[13] and lower (higher) than those for the US, where Foster *et al.* (2001) report growth rates of 2.5% (1.02%) for labour productivity (TFP). Regarding comparisons with developing countries, Aw *et al.* (2003) carried out a similar type of analysis using a multilateral index approach. The problem is that they did not report aggregated results and their coverage of sectors is not fully representative of the whole of manufacturing.[14] This said, they obtained an "unweighted" average TFP growth of 1.5% and 2.3% for Taiwan (1981-1991) and Korea (1983-1993) respectively. More reliable are the numbers reported in Timmer and Szirmai (2000) who, using branch-level data, obtained labour productivity growths of 13.3% for South Korea (1987-1993) and 5.3% for Taiwan (1987-1993). In terms of TFP the results are also more modest: 6.3% for South Korea (1987-1993) and 0.7% for Taiwan (1987-1993). Also, the observation that the phase of faster capital accumulation also coincides with one of the phases of lower productivity growth has been documented for Japanese and US manufacturing (see Ahn, 2003).

It can be inferred from these numbers that, in terms of TFP, Chilean manufacturing has performed relatively well in the long run. Chilean TFP growth is lower than Korea's, similar to Taiwan's, and higher than the two developed countries considered above, implying some movement towards the international frontier although here the comparison is not so straightforward.

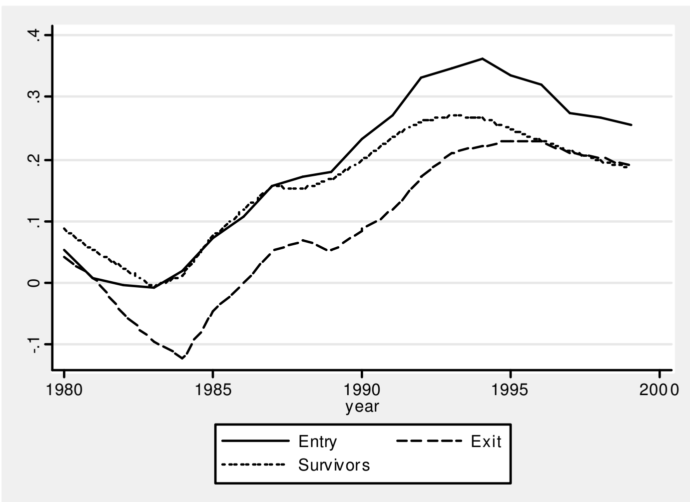
The aggregate figures on the behaviour of the main manufacturing variables are useful to identify the general trends of sector evolution; however, they do not allow us to advance very far in identifying the underlying sources of aggregate manufacturing growth. In order to understand further the micro-foundations of these dynamics, we

[13] For the period 1980-1992 and using the Solow index approach.
[14] They only include the following sectors: textiles, apparel, chemicals, plastics, fabricated metals, electric machinery/electronics and transport equipment.

compute TFP according to the status of the different plants. In order to keep the graph simple we focus on three possible plant states as defined in the previous sections: survivor, entrant or exit.

Figure 5.2 shows the results of this exercise. The left panel captures the median total factor productivity performance of the three different plant status groups. We observe a growing average trend for the three different plant status groups, suggesting that there are systemic forces globally affecting the upward movement of the plants over the whole period. We also note that exiters have lower TFP than entrants that, in turn, have productivity similar to or even higher than that of the survivors. Figure 5.2 tells a story that is consistent with a micro-dynamics where low productive plants die, but are replaced by the arrival of new more productive establishments. This fact clearly points to the importance of the selection process governing productivity growth. These facts are not so far removed from predictions of many recognised models of industrial dynamics, such as Nelson and Winter (1982) and Jovanovic and Greenwood (2001). However, there is a second micro-level driving process behind productivity growth. In the figure, survivor plants exhibit a clear upward trend in productivity, suggesting that improvements in performance by the survivors are another element to be taken into account in explaining productivity. Obviously, these figures point to the qualitative nature of the micro-foundations of aggregate productivity growth, but they do not say anything about the relative importance of the two processes.

Figure 5.2. Total Factor Productivity by Type of Plant



5.2 Productivity Variance

Both the distribution and the average productivity by plant status suggest the presence of high heterogeneity of plant performances. In this section, we take a closer look at this issue by inspecting different measures of productivity spread for both total factor productivity and labour productivity.

The results in Table 5.2 suggest a high level of heterogeneity across plants. The 90-10 interquartile range (IQR) shows plants at the top of the distribution have labour productivities that are 256% above those at bottom. Using labour productivity we see that the spread is higher at the top of the distribution (90-50 IQR) than at the bottom (50-10 IQR). This result is similar to that obtained in Disney *et al.* (2003), whose interpretation is that this finding is consistent with the presence of a lower cut-off point in productivity, determined by the competition process. One important difference from this previous research is that productivity gaps in the Chilean case look much wider than those reported for the UK. For the same 90-10 IQR, Disney *et al.* (2003) obtained a gap of "only" 155%.

For TFP, and according to the 90-10 IQR, we found a narrower gap than was obtained using labour productivity. This means that the spread is higher for labour productivity than TFP. This result would be expected if one considers that labour productivity also includes the volatility in the capital/labour ratios as an additional source of variability. Another way of looking at this is to focus on the last column. This shows the standard deviations of our two productivity measures. As might be expected, labour productivity growth shows a *higher* variance than the TFP index.

Table 5.2
The Spread in Productivity

IQR	95-5	90-10	90-50	50-10	STD
$\ln (Y_t/L_t)$	3.31	2.56	1.48	1.08	1.06
$\ln TFP_{st}$	1.96	1.45	0.64	0.80	0.55

Note: For $\ln (Y_t/L_t)$ and ln TFP the percentile differences were calculated for each year and the numbers in the Table are means across the years

The results in Table 5.2 are somewhat "contaminated" by the presence of plants at different stages of their life cycle and, as a consequence, are not very useful for evaluating the micro-dynamics of TFP growth. Many (if not all) the models of industrial dynamics predict that a given cohort of new plants should be very heterogeneous at the beginning while many of them are involved in experimenting with their capabilities. However, after a time, the poorest units in terms of performance will realise that they are not viable and decide to close down. We look for evidence of this issue by computing a similar table for a specific cohort of new plants. We chose the 1980 cohort because this allows observations over a long period of time. The results are given in Table 5.3.

Table 5.3
The Spread in Productivity: the case of the 1980 Cohort

	95-5	90-10	90-50	50-10	Variance
ln (Y_t/L_t)	3.68	2.42	1.06	1.36	0.95
ln TFP_{st}	1.56	0.97	0.41	0.56	0.45
ln (Y_t/L_t) %	-0.09	-0.06	-0.04	-0.02	-0.01
ln TFP_{st}%	-0.03	-0.02	0.01	-0.03	-0.01

Note: For ln (Y_t/L_t) and ln TFP the percentage differences were calculated for each year and the numbers in the table are means across the years. The growth rate is the yearly average between 1980 and 2000.

The first two rows in Table 5.3 show the spread in productivity in the case of the 1980 entry cohort. In terms of initial spread, the numbers are not particularly different from the average of total manufacturing; however, a better comparison is with the *rest* of manufacturing in the same year. What is interesting is what is shown in the bottom half of the table, which shows the yearly growth rate of the spread over the whole period. Here, for each of the spread measures used in this section, there is a negative trend; suggesting a clear decline in heterogeneity as the cohort ages. This means that, if we focus on the evolution of a particular cohort of plants, heterogeneity shrinks over time (mainly but not only) with the exit of less efficient plants.

So far, we have built up a picture where the aggregate productivity growth is, to some extent, determined by the exit of low productivity plants that are being replaced by the entry of new more efficient ones, and by the improvements made by the group of incumbents. Our findings also suggest that, in contrast to standard vintage models, new entrants are not always better than the incumbents, although they tend to be better than the failures.[15] This is confirmed by the shrinking productivity spread of a cohort of new plants over time.

5.3 Micro-Foundations of Aggregate Productivity Growth: the Within Sector Dynamics

In this sub-section we present the results of the different productivity decompositions described in section 4. Because these decompositions are somewhat sensitive to the importance of exit and entry in total output or employment, we start our discussion by analysing the different market shares by plant status.

Table 5.4 summarises the market shares for entrant, exit and survivor plants during each different sub-period, and uses either employment or output as the measure of scale. The first two rows of the table show the results for the whole period, and their interpretation is as follows: the proportion of employment generated by survivors grew from 35% to 43% over the whole period, suggesting an increasing concentration of employment in larger survivor plants; however, these same numbers also point to a high degree of mobility in the remaining part of the distribution. Plants that closed down over the following 20 years represented 65% of employment in 1979, while plants that entered during the last 20 years were responsible for 56% of the employment in 2000. The importance of entry and exit suggests that the "replacement effects" might have a very important role in explaining productivity growth.

If we move to the other rows of the table we see that the relative importance of entrants and exit plants grows with the duration of the time period under consideration, being lowest in the sub-period 1979-1983. There are two reasons for this: first, a longer time span gives more room for the operation of selection and the exit of low productivity plants; second, a longer period of time also allows for the growth of those efficient new entrants that are able to survive. As a consequence, it is expected that the contribution of net entry to aggregate productivity growth will be affected by the duration of the time

[15] The fact that the entry cohorts are on average better than the rest does not necessarily imply that all entrants are better.

frame under analysis, even if relative productivities among entrants and exiting plants remain stable over time.

Table 5.4
Market Shares for Survivors, Exitors and Entrants

	Employment			Output		
	Survivor	Exit	Entrant	Survivor	Exit	Entrant
1979	35.09	64.91	0.00	47.49	52.51	0.00
2000	43.35	0.00	56.65	57.21	0.00	42.79
1979	79.61	20.39	0.00	85.50	14.50	0.00
1983	89.03	0.00	10.97	91.14	0.00	8.86
1983	73.98	26.02	0.00	81.21	18.79	0.00
1993	63.13	0.00	36.87	70.56	0.00	29.44
1993	56.51	43.49	0.00	61.70	38.30	0.00
2000	66.84	0.00	33.16	72.44	0.00	27.56
1979	61.85	38.15	0.00	71.02	28.98	0.00
1993	59.21	0.00	40.79	66.00	0.00	34.00

Note*:* Entrants are establishments absent in *t-k* and present in *t*; survivors are plants present in both *t-k* and *t*; exits are present in *t-k* but absent in *t*.

The results for output market shares are qualitatively similar, the most significant difference being that the importance of survivors is now higher, while the shares of entrants and exits are lower, with a smaller operating scale for both exit and entrant plants. This means that the contribution of net entry will also be dependent on which type of weights we use, being lower when weighted by output market share. As in the previous section, in what follows we focus on the employment-weighted results, which define a kind of ceiling for the contribution of net entry.[16] In terms of international comparisons we can say that, for the period 1979-1993, the entrant and exit market shares are lower than those reported by Disney *et al.* (2003) for the UK (50% and 42% respectively in 1980/92), and quite similar to those obtained by Aw *et al.* (2001) for some sectors of the Taiwanese manufacturing industry. On the other hand, entrant and exit market shares are larger than those in Foster *et al.* (2001) for US manufacturing (22% and 21% for exits and entrants respectively, during 1977-1987).

[16] Disney et al. (2003) in their results for the UK show that weighting establishments by output rather than employment only marginally reduces the net entry effect, raises the between effect, and reduces the within effect.

Table 5.5

Productivity Decompositions: Labour Productivity and Total Factor Productivity

		BHC			FHK				GR		
		W	B	E	W	B	C	E	W	B	E
Δln (Y_t/L_t)	7900	43.0%	-1.1%	42.0%	43.1%	9.3%	-8.6%	40.3%	38.5%	2.7%	42.7%
	7983	0.5%	3.9%	5.4%	0.6%	3.4%	0.5%	5.3%	0.8%	2.6%	6.5%
	8393	17.8%	-6.9%	10.1%	17.7%	-0.4%	-5.9%	9.6%	14.6%	-2.3%	8.7%
	9300	24.7%	2.0%	26.5%	24.8%	6.3%	-3.2%	25.3%	23.2%	2.4%	27.6%
	7993	18.3%	-3.0%	15.5%	18.3%	3.0%	-5.4%	14.9%	15.4%	0.3%	15.2%
	(%)	59.46%	-9.86%	50.40%	59.3%	9.8%	-17.5%	48.5%	49.9%	0.9%	49.2%
Δln TFP_{st}	7900	5.0%	3.5%	8.5%	5.0%	1.2%	2.3%	8.5%	6.1%	1.3%	9.6%
	7983	-2.9%	1.3%	0.8%	-2.9%	-1.1%	2.5%	0.6%	-1.7%	-0.9%	1.8%
	8393	9.1%	2.1%	5.8%	9.0%	2.5%	-0.5%	6.0%	8.7%	3.0%	5.2%
	9300	-1.1%	0.1%	1.9%	-1.1%	-0.2%	0.3%	2.0%	-0.9%	-0.8%	2.7%
	7993	6.1%	3.4%	6.6%	6.1%	1.4%	2.1%	6.6%	7.1%	2.1%	7.0%
	(%)	38.07%	21.13%	40.81%	38.0%	8.7%	12.7%	40.6%	43.7%	13.1%	43.2%

Note: The decompositions were first computed at 3-digit ISIC level and then aggregated using the sector shares in total manufacturing, all employment weighted. W: Within plant effect; B: Between plants; C: Covariance Effects; E: Net Entry. BHC is the Baily, Huelten and Campbell decomposition; FHK the Foster, Haltiwagner and Kirzan methodology; and finally, GR that of Griliches and Regev.

Table 5.5 shows the results of the productivity decompositions using the different approaches discussed in section 4. The first columns present the results of using the BHC method (Baily *et al.,* 1992) (BHC, equation 4.4). If we focus on the long-run results (the peak to peak period 1979-1993), the importance of net entry is remarkable: the replacement of inefficient plants by new more efficient entrants explains, respectively, 50% of labour productivity growth and 40% of TFP growth. The within-plant improvements, on the other hand, are relatively more important for labour productivity growth (60%), but they still contribute 40% to TFP growth. The between component, which is negative but very small for labour productivity growth, becomes positive and important for both TFP indices, suggesting that market selection is generating faster growth among more efficient plants.

If we focus on the different sub-periods, we find that during the contraction of 1979-83 the within component of TFP growth (which was always procyclical) is always balanced by net entry and between components. Indeed, while the plant-level TFP clearly declined, the net entry and between elements were positive, compensating for the negative impact of the recessions. This means that plant-level TFP was always more procyclical than aggregate TFP. These findings are reversed when we move to a faster growth period, for instance the recovery of 1983-93. Here, both market shares and net entry reallocations are less significant, with a stronger within effect. These results might suggest the operation of some "cleansing" effect during the recession generated by both a higher death rate of less efficient plants and, probably, the creation of very efficient new entrants. It is also important that shorter periods of time also show an absolute lower contribution of net entry (as during 1979-83 and also 1993-2000). This is to be expected from what we know about the behaviour of market shares according to plant status. However, because these different sub-periods are also affected by slowdowns in the business cycle, it is important to compare the relative performance of entrants and exit plants regarding the within performance of survivors.

The situation is rather different in the last period, which is characterised by a low growth rate (including a mild recession in 1999), and very high rates of capital formation coupled with very high rates of employment destruction. In terms of the macroeconomic context, this is a period also characterised by some negative external shocks plus a relatively "strong" peso. During this phase, while labour productivity grew, TFP was stagnant. One reason for this bad performance was a decline in TFP by the survivors (the within-plant effect), but also interesting is the negative contribution of net entry effects. This is consistent with a relatively worse performance from the entrants rather than improvement in the exiting plants (see Figure 5.2). We do not have an absolute explanation for this, but a plausible interpretation could be that the particularly high rate of investment during this period is an indication that new technologies were being embodied in the new plants. Indeed, these new plants were much more capital intensive than entrant plants in the previous sub-periods. These new technologies typically would require a series of costs of adjustment (such as for the re-training of the new workforce, learning-by-doing of the new codes, etc.) that may well have reduced the initial efficiency of these new plants.[17,18] Finally, during this last sub-period the between component makes a positive contribution to aggregate productivity growth, suggesting a reallocation of market share to the most efficient survivors.

[17] This argument can be used in order to explain at least part of the decline by the survivors.

[18] For empirical evidence on the costs of adoption of new technologies see Enos (1997). For a theoretical analysis of this problem and its empirical illustration in the case of the US slowdown in productivity growth see Jovanovic and Greenwood (2001).

As discussed above, using the BHC decomposition can bias the results for the net entry effect because the method does not distinguish the importance of relative productivity between entrants and exitors. Therefore, the results could be affected by any difference in market shares between entries and exits. In order to assess the significance of this problem, we applied the correction suggested by Haltiwagner (1997) (FHK, equation 4.6). The results can be seen in the four centre columns of Table 5.5.

A simple comparison between the BHC and FHK columns in Tables 5.5 suggests that the results are pretty stable. The long-run contribution of net entry is 58% in the case of labour productivity, while the corresponding values for the TFP index is 38%. In the case of labour productivity there is now exists a relatively large negative covariance term, a result also found by Foster *et al.* (2001) and Disney *et al.* (2003), who explained it as “downsizing”. In plants that try to increase efficiency by closing down some operations and firing part of their workforce, we would clearly expect a negative correlation between change in market share (measured by employment) and future labour productivity growth. In the case of TFP, the covariance term is positive, indicating a positive correlation between market share reallocations and productivity growth in the group of survivors. This covariance term is very important, explaining between 30% and 13% of aggregate TFP growth. As before, we also observe a compensating effect of the covariance and net entry components during the 1979-83 recessions. In summary, the results do not appear to be greatly affected by any bias in the measurement of the net entry component.

One remaining problem with the two methods used is that they are vulnerable to measurement errors, either in inputs or in outputs. Griliches and Regev (1995) suggest a method that averages market shares and productivity over the period under analysis, which is less vulnerable to these problems. The disadvantage is that there is now some contamination in the way both the within and between components are measured (GR, equation 4.8).

The results of the third decomposition can be seen in the last column of Table 5.5. If we focus on the long-run results, we can infer that these are again relatively stable and similar to the two previous exercises. Net entry explains 50% of labour productivity growth, and 43% of TFP. Again, as was observed in the previous results for the 1979-83 recession, while the within component of TFP is procyclical, the combined effects of the between and net entry components are positive, (slightly) balancing the aggregate impact of the recession. The importance of the within component also increases during the period of fast growth and (for TFP) the between component is positive, a sign of a positive correlation between TFP growth and changes in market shares. It therefore does not seem likely that the results in the previous tables are biased by any serious measurement errors in the variables. The major difference between this set of results and the previous two is the growth in the importance of the within component of TFP growth (it increases from 38% to almost 43%). This is explained by the fact that part of the between term is being now allocated to the within component (and the between term on the other hand declines).

In summary, the long-run results point to the operation of three clearly identifiable sources of aggregate productivity growth: within-plant improvements by the incumbents; market share reallocation to more efficient survivors; and replacement effects generated by the entry of new establishments replacing inefficient exits. The results for TFP are remarkable using the most "robust" decomposition we find that that about 43% of the aggregate productivity growth is explained by within-plant improvements, an additional 43% by net entry, and the remaining 15% by market share reallocation among the survivors. These values change over the business cycle in a rather predictable way: the plant-level improvements are procyclical, while the combined effects of market-share reallocations plus net entry tend to be countercyclical. As a consequence aggregate productivity is slightly less procyclical than plant-level TFP.

5.4 Micro-Foundations of Aggregate Productivity Growth: International Comparisons

Although previous research differs in terms of how TFP was calculated, the decomposition method under use, and even the weights applied for estimating market shares, we still consider that international comparisons are a useful tool to benchmark the country results and to validate that our findings are within some "admissible" ranges. The results of the international comparisons are presented in Table 5.6.

Regarding labor productivity, the within component is larger in the US (similar to the average of OECD countries) than either the UK or Chile, countries that have a very similar proportions of within and net entry components. Estonia is in between. For TFP, the results again show a higher share of the within effect in the US, similar to the average of the OECD countries while comparisons between the UK and Chile indicate that the importance of the within component is much higher in Chile than the UK, where the between and net-entry effects are more important. For TFP, the Chilean results look closer to those for Estonia, with a small bias in the Chilean case towards net entry and market share reallocations, and a small bias towards within plant improvements in Estonia. Finally, the comparisons between Taiwan and Chile suggest higher net entry and between components in Chile and relatively much more important within-plant improvements in Taiwan.

Table 5.6.
Productivity Decompositions: International Comparisons

	Time Period	Method	Productivity	Total	Within	Between	Net entry	Weight
US	1977-1987	GR	Labour	23.0%	69.0%	1.0%	30.0%	Employment
UK	1980-1992	GR	Labour	54.2%	47.0%	-1.0%	53.0%	Employment
OECD	1987-1992	GR	Labour	15.3%	67.7%	7.6%	20.4%	Employment
Estonia	1997-2001	GR	Labour	46.7%	59.2%	-2.0%	42.8%	Employment
Chile	1979-1993	GR	Labour	33.6 %	49.9%	0.9%	49.2%	Employment
US	1977-1987	GR	Solow	10.2%	65.0%	10.0%	25.0%	Gross Output
UK	1980-1992	GR	Solow	13.9%	18.0%	23.0%	58.0%	Employment
OECD	1987-1992	GR	Solow	2.3%	70.2%	23.6%	6.2%	Employment
Estonia	1997-2001	GR	Solow	36.6%	51.3%	11.6%	37.2%	Employment
Chile	1979-1993	GR	Solow	16.1 %	43.7%	13.1%	43.2%	Employment
Taiwan	1981-1991	GR	Multilateral	19.8%	62.0%	3.0%	35.0%	Gross Output

Note: The source of US data is Foster, *et al.* (2001); the source of UK data is Disney *et al.* (2003) and the source of Taiwan data is Aw *et al.* (2001). The "OECD" data refer to an average over Finland, France, Italy, Netherlands, Portugal, UK, USA for labour productivity and to an average over Finland, France, Italy, Netherlands and UK in the case of TFP. These data are taken from Barnes *et al.* (2001). The source of Estonian data is Masso *et al.* (2004).

An interesting way of analysing Table 5.6 is to compare Chile with the other two developing countries in the sample and with the averages for the "developed" world. From a comparison between Chile and the OECD countries it becomes clear that the influence of net entry and market share reallocation as a source of aggregate productivity growth is much stronger for Chile. This result is robust to using either labour or TFP. In addition, the Chilean bias toward selection is also shared by the other two developing countries in our "sample": Taiwan and Estonia. However, both Estonia and Taiwan have a larger share of the within-plant component than Chile.

In summary, it seems that Chile is not an outlier. Its performance is well within the ranges of the, somewhat scant, empirical evidence available to us. Using relatively "comparable" methodologies for computing TFP and for decomposition analysis, we found that Chile (and the other developing countries in the table) has a relatively stronger bias towards selection, mainly due to the influence of net entry, while the developed countries show greater importance of within-plant improvements.

It is beyond the scope of this research to "explain" the reasons for these differences. However, some hypotheses can be advanced. In the first instance, there are methodological differences: the time length for the analysis differs across the countries being considered and also the countries are at different points in their business cycle. Regarding the first issue, we have the shortest time length in the case of the OECD countries and Estonia. We know that a short time length increases the importance of the within component of productivity growth. Although this might be the answer in relation to Estonia, we can see that the numbers for the OECD average (with five year time spans) and the US (with 10 year spans) are very similar. In relation to differences in the business cycle, we know that for the OECD countries the years 1979-92 were mainly a period of recovery, which would inflate the importance of the within component; however, this was also a phase of recovery for Estonia, indicating that a lower influence of within-improvement (at least in this case) is not due to the influence of the business cycle.

An alternative way to justify the importance of selection in developing countries concerns the nature of the macroeconomic regimes in operation in these economies. In contrast to the OECD countries, it has been suggested that the growth process in the developing countries is much more volatile, the length of each cycle is shorter, and the magnitude of the movements around it is greater -Katz (2001). As a consequence of this more uncertain environment, agents pay more attention to flexibility than long-run commitment to the management of their business. This propensity to avoid sunk investments in improvements at plant level might be a reason for the lower impact of the within component in the developing world.

A second hypothesis is that the bias towards selection in the case of developing countries is a natural result of the process of development. One stylised fact pointed to by Kuznets (1971) is that there is a negative relationship between self-employment and income per capita. This result has been interpreted as an indicator that the degree of entrepreneurship of a given society will decline with its degree of development (see Carree *et al.,* 2002). There are two complementary explanations for this fact. First, as soon as a society develops, the capital intensity and entry barriers for many productive activities increase. Second, the increased labour productivity leads to an increase in wages and in the opportunity cost of self-employment in comparison to salaried work (see Lucas, 1978). However, it is worth mentioning that while these explanations might justify the larger market shares of entrant and exit plants in developing countries, the larger contribution of selection also requires that entrant plants have higher productivity than the average and/or that exit plants are well below the average.

A final set of hypotheses is related to a potentially larger influence of market imperfections in the developing countries (not only regarding products, but also input markets, lack of infrastructure and institutional failures[19]). These imperfections impose a higher productivity threshold that plants must overcome in order to compensate for these higher costs.[20] Because of this we would expect in the OECD countries the

[19] This institutional explanation is the one favoured by Barnes et al. (2001) to explain the differences in net entry within a sample of OECD countries.
[20] We mean here productivity relative to the incumbents'.

presence of a longer tail of unproductive plants, which would not be able to survive in the conditions of the developing world. But how would all of this affect net entry?

Entering plants in developing countries would have higher (relative) productivity than entering plants in the OECD. This would increase the importance of the entry effect in the developing world. However, for the same reason we would also expect fewer entrants, something that would reduce the importance of entry unless entrant firms are relatively much larger. Meanwhile, exiting plants in the OECD countries would have lower (relative) productivity than the exiting plants in the developing world. If we expect a higher (relative) productivity for exiting plants in the developing countries this would reduce the contribution of exit to aggregate productivity growth. Against this we would have more exits in the developing countries, which would raise the exit effect in an absolute manner. Putting all of this together, the prediction about the impact of a higher productivity threshold in the developing countries on the importance of net entry and selection is ambiguous. However it seems that, at least in the Chilean case, the larger contribution of net entry is mainly due to two factors: larger size of entrants together with a slightly higher than average TFP coupled with smaller size of exits together with a clearly lower than average TFP.

5.5 Micro-Foundations of Aggregate Productivity Growth: Net entry effect

The results for net entry in the previous section are affected by the length of the time period. This is due to the fact that in each of the decompositions the entering and exiting plants are not really entry and exit cohorts. In the above analysis, exit plants are those that appear in production in period $t-k$ but not in t, hence this is a set of plants that are either exiting in $t-k+1$ or in any one of the following years up to $t-1$. On the other hand, entrants are plants that are in production in t, but could have entered in any year between $t-k+1$ and t. Because of these definitions, a new entrant in our analysis is a plant that has entered and been in operation for an average of $k/2$ years. Similarly, firms that exit will have, again on average, remained in operation $k/2$ years after the point last observed in the analysis. As a consequence, if entrant plants grow in size over time, while exit plants shrink just before exit, a longer interval of time will inflate the market shares of entrants and exits, increasing the contribution of net entry.

It is important to note that the importance of net entry depends not only on the market shares of entrants and exits, but also on their relative productivities. If the time span is quite short, there will be exiting plants that do not show any decline in productivity before exiting[21] co-existing with entrants that have not yet embarked on any learning-by-doing process, displaying as a consequence a low productivity phase. Thus the contribution of net entry could be negative in the short run.

Although the Table 5.5 covered time periods of different lengths, they do not help here because the numbers are contaminated by the different phases of the business cycle. Therefore we need first to establish the time frame as 1979-1993, which roughly corresponds to the peak-to-peak phase of the business cycle, and then apply Disney *et al.*'s methodology (2003), calculating the decompositions for sequentially shorter intervals of time. The results of this exercise are presented in Table 5.7, where we show both the productivity growth rate and the corresponding proportion explained by net entry.

Table 5.7

The Contribution of Net Entry to Productivity Growth, by Length of Period (%)

	7993	8093	8193	8293	8393	8493	8593	8693	8793	8893	8993	9093	9193	9293
%	0.49	0.51	0.63	0.46	0.41	0.46	0.43	0.53	0.35	0.3	0.19	0.18	0.21	0.09
$\Delta\ln(Y_t/L_t)$	0.33	0.2	0.1	0.32	0.25	0.27	0.29	0.12	0.21	0.18	0.15	0.16	0.07	0
%	0.43	0.35	0.37	0.34	0.3	0.31	0.29	0.25	0.33	0.33	0.37	0.48	2.55	-0.23
$\Delta\ln TFP_{st}$	0.17	0.14	0.12	0.17	0.19	0.14	0.13	0.06	0.06	0.04	0.03	0.01	-0.01	-0.03

Note*:* The decompositions are based on the GR method. 7993 = 1979-1993 (etc.).

The top panel of Table 5.7 shows the contribution of net entry to labour productivity growth. We can see that when the interval of time is 6 years or more, there is remarkable stability in the contribution of net entry, which is always above 40% and fluctuates between 63% and 43%. However, shorter time periods produce a very smooth decline in the contribution of net entry, to only 9% of labour productivity growth when the transition is only one year.

In the case of TFP, the contribution of net entry is more stable. Even for periods of time as short as three years, net entry represents more than 40% of aggregate productivity growth and its values are stable over longer intervals. The pattern in this case resembles an inverted U function: the contribution of net entry first declines from 43% to 25% when we shorten the time length and then moves up again to 48% with a lag of only three years.

In summary, the contribution of net entry to labour productivity growth is a time-dependent indicator, where a longer time span tends to increase the importance of net entry. However, net entry shares become more "immune" to this effect when we focus on TFP and take intervals of longer than three to five years. Shorter periods of time also display more volatility, not allowing clear identification of any particular trend. Thus, the contribution of net entry is not a simple artefact of the time period chosen for the analysis: its importance remains high even when working with intervals of quite short length.

In order to study in more detail the impact of post-entry performance of new plants on total entry contribution, we split the contribution of entrants to productivity, into the contributions of successive cohorts of entrants. As Disney *et al.* (2003) suggest, if the entry effect is due mostly to growth subsequent to entry, then the contribution of the longer-established cohorts would be dominant. The results of this exercise are shown in Table 5.8.

Table 5.8
Productivity by Entry Cohorts, from GR decomposition 1979-1993

	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	Total
$\Delta\ln (Y_t/L_t)$(a)	-0.08	0.24	0.21	0.27	0.04	0.10	0.12	0.21	0.17	0.29	-0.12	0.10	0.21	0.01	0.13
$\Delta\ln (Y_t/L_t)$(b)%	0.4	0.8	0.4	1.1	0.9	0.4	0.8	1.2	0.9	1.8	0.3	0.9	1.3	0.3	11.4
$\Delta\ln (Y_t/L_t)$(c)%	3.1	10.3	13.4	22.9	30.8	34.7	41.4	51.9	59.4	75.4	77.7	85.7	97.5	100.0	
$\Delta\ln TFP_{st}$(a)	0.15	0.15	0.16	0.07	0.09	0.14	0.12	0.17	0.05	0.16	0.08	0.25	0.22	0.26	0.15
$\Delta\ln TFP_{st}$(b)%	-0.4	0.8	0.6	-0.3	0.0	0.3	0.9	0.3	0.8	0.1	0.4	1.7	-0.2	1.9	6.9
$\Delta\ln TFP_{st}$(c)%	-5.8	6.2	14.7	10.5	11.1	15.3	28.5	33.3	45.0	46.3	51.3	75.4	72.6	100.3	

Note*:* Rows (a) are the mean relative productivity of each entry cohort relative to average productivity over the growth period. Rows (b) are the third element in (4.9) for each cohort. Rows (c) are the accumulated contribution of each cohort

[21] Griliches and Regev (1995) observed this in relation to Israeli manufacturing and named it the "shadow of death".

For each of the productivity measures, rows (a) in Table 5.8 show the (unweighted) relative productivity of each entry cohort relative to manufacturing productivity averaged over the growth period. If we focus on the TFP results first, we can see that the cohorts with the largest TFP gains are the most recent ones. While the relative TFP of the 1993 entry cohort was about 20% above the period average, the relative TFP of the survivors from the 1980 cohort was 15% above the manufacturing average, depending on the TFP index being analysed. The results for labour productivity are somewhat closer to what was originally expected. That is, the greatest gains in labour productivity are concentrated in the oldest cohorts. Taken together these results seem to indicate that new plants are more efficient (on average) at the time of entry; after this there is not much evidence of growth or improvement. However, it also seems that this initial advantage also positively influences the accumulation of capacity and more sales, leading to an increase in labour productivity.

The analysis is not straightforward however, because the contribution of each entry cohort to total entry effect is also affected by the cohort's share in total employment. If we focus our analysis on the contribution of the entry cohorts to total entry effect (rows (b) and (c)), we find that for the TFP, the initial advantage of the youngest cohorts becomes more attenuated, although remains considerable: about 36% of the total entry effect is due to those cohorts entering before 1986, while the remaining 64% is due to the contribution of the post-1986 entry cohorts. The results also differ in the case of labour productivity, where both the old and the recent cohorts contribute about 50% of the total labour productivity growth generated by the entry effect. That is, although many entrants are very efficient but small, they are able to grow, making a remarkable contribution to both TFP at the time of entry, and labour productivity over time.

In conclusion, it does not seem that learning or growth effects in the longer surviving establishments in the various cohorts dominate the entry term. The youngest cohorts not the long-surviving establishments make the largest contribution to the total net entry effect. In terms of relative TFP the differences are even more remarkable. The youngest cohorts clearly show higher productivity than average. This result does not rule out the presence of learning effects; however, if one considers that the initial productivity of an entrant is the result of its potential productivity (in the case of Chile mainly driven by the embodied technical change spilling over from the international frontier) and the efficiency with which this technology is adopted (which is affected by experience and learning), our results suggest only that there is high productivity at entry, and that effect of initial "lack" of experience is not so strong as to offset the initial advantages of the new (embodied) technology. We are led to conclude, therefore, that the importance of the net entry effects obtained in many of the decompositions is a genuine result, and is not contaminated to any major degree by the post-entry growth and learning of mature entrants. That is, there seems to be a fixed effect governing the initial productivity of the entrants, and this fixed effect dominates the measurement of productivity. It is worth noting that this result is very close to the predictions of the standard vintage capital model, where the new plants are those that embody the most recent technologies and then become the engines of growth.

5.6 Movements in the Productivity Distribution of Plants

The productivity decompositions in the previous section give only a partial picture of the productivity dynamics in Chilean manufacturing. They are static in nature, leading to an unsatisfactory treatment of the heterogeneity existing within each stratum of survival, entrant and exit firms. We need to investigate further the importance of net entry, in particular in relation to the findings in the previous section. Are the initial productivity advantages of new plants shared by all the members of the entry cohort? Or are they generated by the presence of a sub-group of entrants with very high initial productivity, which more than compensates for the lower efficiency of the remaining members of the entry cohort? If it is true that the results in the previous section are driven by a plant vintage model, should we not also observe the incumbents' relative productivity continuously move downwards over time?

To answer these questions we need to see how the ranking of plants changes across the productivity distribution, and over time. Baily *et al.* (1992) and Haskel (2000) do this by building transition matrices.

In order to build a transition matrix the plants in the sample must be ranked by relative productivity in each year, and sorted into quintiles. From this we can compute the fractions of plants in the sample that make each alternative movement among quintiles, by each pair of years. Of course, over time incumbent plants may exit from the industry and new plants arrive; as a consequence two additional states must be considered: births and deaths. A transition matrix can give a lot of information about productivity dynamics. For example, for the plants in the top quintile in their own industry at time t, we can see what fraction were also in the top quintile in their industry in year $t+k$. The fractions in the second, third, fourth and fifth quintiles can also be determined. Some of the incumbent plants at time t will have been closed down in $t+k$, then we will have the transition to death. Finally, we can find how those plants that enter the industry between t and $t+k$ are distributed across the productivity quintiles in $t+k$. Are they all close to the top quintile as the simple vintage capital model would predict?

Table 5.9 shows the plant transition matrix over the short run. In order to select a relatively normal short run period we focused on 1992 and 1993, which were close to full capacity in manufacturing. The cells have all been weighted by employment size.

Table 5.9
Total Factor Productivity Transition Matrix, all plants, 1992-1993, Weighted by Employment (highest productivity, quintile 1; lowest quintile 5)

Solow Index

Quintiles 1992	Quintiles 1992	1993 1	2	3	4	5	Death	Total
1	1	71.6	9.7	1.5	2.4	6.3	3.3	100.0
2	2	22.5	54.7	11.5	5.6	9.3	5.1	100.0
3	3	4.8	25.2	42.1	19.8	13.6	6.4	100.0
4	4	0.6	5.0	22.8	50.8	9.9	13.1	100.0
5	5	4.0	6.5	7.1	15.2	63.6	7.7	100.0
Entry	Entry	11.8	23.7	22.4	26.7	15.2	0.0	100.0

Note: The top left cell shows the employment-weighted fraction of plants beginning in the top TFP quintile in 1992 which remained in the top TFP quintile in 1993. The second cell of the top row shows the employment-weighted fraction of plants beginning in the top TFP quintile in 1992 which were in the second productivity quintile in 1993. The rest of the body of the table reads analogously. The top cell of the last column shows the employment-weighted fraction of plants beginning in the top TFP quintile in 1992 which exited at some point between 1992 and 1993. The bottom left-hand cell shows the employment-weighted fraction of plants ending up in the top TFP quintile in 1993 which entered at some point between 1992 and 1993.

To show how the matrix works, start with the cell in the first row and first column in the left-side panel. This cell reads as follows: of the plants that were in the first quintile in 1992, a weighted 71% of them were in the first quintile in 1993. The following cells of the first row indicate that of the plants that were in the first quintile in 1992, 9% had moved down to the second quintile by 1993, a further 1.5% had moved down to the third quintile, 2% had declined to the fourth quintile, 6% had descended to the fifth quintile, and 3% of them had exited. There is then a large persistence in the short run for those plants located in the top quintile

Now consider the bottom quintile in 1992: in the right cell we find that 63% of the plants (weighted by employment) remained in the bottom of quintile one year later. Although still high, the persistence here is lower than in the case for the top quintile. Indeed, of the plants in the bottom of the distribution in 1992, 7.3% exit the market, but 4% move to the top quintile. There is lower persistence at the bottom of the distribution in the short run (at least in comparison to the top quintile). However this is to some extent to be expected due to the fact that these plants have the opportunity to close down as well as to move up.

The middle cells seem to show lower persistence. Indeed, of the plants in second, third and fourth quintiles in 1992, 52%, 42% and 50% respectively were in the same position one year later. Of the rest we can see that some were able to move upwards in the productivity distribution, while others move downwards or exited. However, it is important to note that this greater mobility “in the middle” is in part a statistical result since plants in the middle groups have more cells to move into.

The “death” column in Table 5.9 refer to the exit probabilities in the short run. We can see that there is a (non-monotonic) pattern where the fraction of plants that exit the industry grows when we move downwards in the initial productivity ranking. That is, short-run exit rates are 3% in the case of plants in the top quintile, 5% for plants in the second quintile, 6% for plants in the third quintile, 13% for those in the fourth quintile, declining to 7.4% for those in the fifth quintile one year before.

Finally, the "birth" row in Table 3.15 shows the relative productivity of those plants that entered the industry between 1992 and 1993. Here we can see that there are as many entrants to the top of the distribution in 1993 (11.7%) as to the bottom of the distribution (15.2%), but the vast majority of entrants were allocated to the middle cells. That is, the typical entrant plant is closer to the "average" in the industry than was expected.

Table 5.10
Total Factor Productivity Transition Matrix, all plants, 1979-1993, Weighted by Employment (highest productivity, quintile 1; lowest quintile 5)
Solow Index

Quintiles 1979	Quintiles 1979	1993 1	2	3	4	5	Death	Total
1	1	26.9	9.6	5.5	4.8	6.7	46.5	100.0
2	2	6.6	11.2	9.7	8.9	6.0	57.6	100.0
3	3	4.3	8.4	10.3	9.7	5.4	61.9	100.0
4	4	2.7	5.4	7.6	10.4	7.8	66.1	100.0
5	5	8.7	5.8	4.0	5.9	20.6	55.1	100.0
Entry	Entry	16.9	21.0	22.5	21.3	18.2	0.0	100.0

Note: As for Table 5.9, substituting 1979 for 1992 as the initial year.

Table 5.10, which summarises the results of the long-run transitions, presents a different picture. We focus here on the period 1979-93, which, according to our numbers, also corresponds to the peak to peak of the manufacturing business cycle. The results for the top quintile show that the degree of persistence now is much lower. Of the plants in the top quintile in 1979, about 27% of them were still in the top quintile in 1993, 9% had moved down one quintile, 5% declined to the third quintile, 5% went down to the fourth quintile, and 7% ended in the fifth quintile. In addition, a quite surprising 46% of the top plants had exited.

It is worth noting here that these figures are very similar to those reported by Haskel (2000) for the UK in 1980-90. Indeed, for this 10-year period Haskel found that the persistence in the top group was 31% and that exits from the top were 50%. The first reaction to these figures is to assume that productivity is not a good predictor of exit. However, we know from the year-to-year transitions that plants at the bottom were two to three times more likely to fail than plants at the top. A more plausible assumption would be that the high exit rate of top plants in the long-run transitions is due to those plants moving down in the productivity distribution over the 1979-1993 time period, as is suggested by the year-to-year transitions.

Continuing with the analysis of the long-run transitions, we find that of those plants at the bottom of the distribution in 1979, only 20% were at the bottom in 1993: 53% had exited and 8% had managed move up to the top quintile of the 1993 productivity distribution. For the plants in the middle quintiles the results are similar to the previous ones, that is, that some of the plants in the middle quintiles had managed to move up, but about 60% in the end had failed. Regarding the entrant plants, about 17% entered at the top of the distribution in 1993, 18% were at the bottom, while the rest were evenly spread across the middle quintiles.

Despite the "average" TFP gains by the entrants found in the previous section, when analysing productivity dynamics, we find that the evidence supporting a standard vintage model is small. The quite considerable number of new plants that entered the top quintile of the distribution, coupled with the fact that there is a "sliding down" effect of the top quintile plants in the long-run transitions would support this model. However, three important factors act against it: first, there are many bad entrants located in the middle or the bottom quintiles of the productivity distribution; second, there is relatively high persistence, at the top of the distribution, and even in the case of the long-run transitions;[22] third, a quite significant number of plants in the middle and even the bottom of the distribution at the beginning were able to move up to the top. This means that, although the concept of vintage seems reasonable, there are many old plants that are able to re-tool and upgrade. It is important to say here that it is unlikely that this would be the result of a simple mechanistic learning-by-doing process (which would be expected in younger rather than older plants), but rather it would arise from active search and investment. In other words, it seems that many of the plants at the top of the distribution suffered a process of productivity erosion over time (possibly due to periods

[22] This persistence is not consistent with the standard vintage plant model: as new plants embodied better technology, older plants inevitably move down the productivity distribution.

of inaction to avoid investment sunk costs); after a time many of these plants fail and exit, but a remarkable fraction of them are able to re-invent themselves.[23]

In summary, the results of this section point to the presence of a much more complex industrial dynamics model. These dynamics can be only partially explained by vintage effects; “advantages of birthright” (or fixed effects) and the results of active search processes of innovation also play a part.

5.7 Microfoundations of Aggregate Productivity Growth: the manufacturing branches

In this section we look at the different branches of Chilean manufacturing in order to see if our previous results are applicable to most sub-sectors or if they are severely biased by the influence of certain specific but important activities. It should be remembered that Chilean manufacturing is very specialised in the processing of natural resources and foodstuffs. The importance of these sectors could be hiding differences in other activities, that may be less important in terms of output or employment, but dynamic. In what follows, we focus on the peak-to-peak phase of the business cycle and present the results for our three different measures of productivity. In all cases we use the Griliches and Regev decomposition because it appears more robust to measurement errors.

The detailed results of the analysis are shown in Crespi (2005). The main results are as follows. The three sectors with the highest labour productivity growth are iron and steel (371), beverages (313) and furniture (332),[24] all of which are related to the processing of natural resources. In these three sectors the importance of net entry as a driving force of sector labour productivity growth is never lower than 50%. The three worst performing sectors are leather products (323), rubber products (354) and plastics (356). The main reason for their poor performance is the within component of labour productivity growth. One way to generalise these findings is to compute the share of each component

[23] Note the closeness of these results to the prediction of the routinised Schumpeterian regime model. In this model (see Nelson and Winter, 1982) the inaction periods and the adjustment costs are justified by the idea of bounded rationality and routines. We consider that similar results can be explained without making such restrictive behavioural assumptions.

in labour productivity growth, and calculate the correlation between labour productivity growth and the importance of each component. If we do this for labour productivity, the correlation coefficient between the importance of net entry and labour productivity growth is positive (0.38), but the within component is negative and very low (-0.18). Although these results are non-significant they point to the fact that replacement effects are a major driving force underlying labour productivity growth.

In terms of the results relating to TFP, the three sectors with the highest TFP growth are iron and steel (371), furniture (332) and beverages (313). These are the sectors that enjoyed rapid labour productivity growth. However, the sources of growth differ. In iron and steel and beverages growth is dominated by within-plant improvements, while in furniture the largest element comes from net entry effects. The three worst sectors are basic chemicals (351), foodstuff (311) and plastics (356).

Table 5.11 shows the top three sectors in terms of productivity growth compared with the three worst sectors. Several conclusions can be drawn. First, even in very scale-intensive sectors such as iron and steel the net entry contribution to TFP growth is very important. Second, the importance of the net entry component of productivity growth is stronger in sectors with low rather than high productivity growth. In contrast, the within component is more important in sectors with high productivity growth. Finally, the within component tends to be higher in scale-intensive sectors. However, it should be emphasised that the differences across sectors were lower than expected.

[24] We decided not to consider oil derivatives because the high labour productivity growth in this sector is mainly due to the influence of one particularly capital-intensive entrant in 1984. Hence we did not consider that this sector showed a proper real long-run trend.

Table 5.11

TFP Productivity Decompositions: Main 3-digit ISIC Industries

Sector	K/L Index	Total	Within	Between	Net Entry
Top 3					
Iron & Steel	0.38	66.7	61.6%	-3.9%	42.1%
Furniture	0.07	62.2	25.9%	4.2%	69.9%
Beverages	0.42	54.1	38.1%	25.3%	36.8%
Bottom 3					
Basic Chemicals	1.00	17.7	15.3%	21.5%	63.5%
Foodstuffs	0.16	15.3	34.6%	22.9%	42.5%
Plastics	0.21	10.4	12.5%	7.7%	79.8%

Note: The Within, Between and Net entry columns are shares of TFP growth. The GR decomposition method is used, and productivity is given using the Solow Index. The growth period is 1979-93.

One way to summarise the results across sectors is by computing the unweighted averages across them and comparing the results with those for all manufacturing (see Table 5.12). While the weighted and unweighted results are very similar in the case of labour productivity growth, there are important differences in relation to TFP. The unweighted net entry effects are perceptibly larger than the weighted ones. Indeed, in the case of TFP the importance of the net entry share in long-run TFP growth increases from 43% to 58%. These results can be explained by the importance of the net entry effect in a series of small (in terms of contribution to manufacturing output or employment), mainly labour-intensive sectors such as textiles, leather products, furniture and scientific instruments, and also by the presence of some capital-intensive (although not very scale-intensive) sectors such as plastics, ceramics and glass. The other side of the increase in net entry effect is the decline in contribution of the within effect.

In summary, the importance of the entry effects in the aggregate results does not seem to be a consequence of a composition problem across sectors, nor do they appear to be severely affected by the importance of some particularly large sectors. The significance of net entry as a source of aggregate productivity growth is pervasive over a large number of sectors, leading to the conclusion that our aggregate results are fairly robust.

Table 5.12
Productivity Decompositions: Sources of productivity growth (%) across sectors, weighted vs. unweighted results

		Within	Between	Net entry
$\Delta\ln(Y_t/L_t)$	Weighted	49.9%	0.9%	49.2%
	Unweighted	55.1%	-2.5%	47.4%
$\Delta\ln TFP_{st}$	Weighted	43.7%	13.1%	43.2%
	Unweighted	31.6%	11.0%	57.4%

Note: The GR decomposition method is used, and the growth period is 1979-93. Sector results weighted by employment

6 Openness, Foreign Competition and Total Factor Productivity Growth

The Chilean economy underwent major structural reforms during the second half of the '70s, among others one of the most dramatic ones has been trade liberalisation and the sudden exposure of the manufacturing sector to international trade. Indeed, during the 1974 to 1979 period, Chile implemented programmes of major trade liberalisation, deregulation, privatisation and labour market reforms. In the case of trade liberalisation, the country eliminated most of its non-tariff barriers and in 1979 reduced tariff rates, which had often been more than 100% in 1974, to a uniform cross-industry 10% ad-valorem tariff. Chile's commitment to free trade persisted during the 1980s, except for a transitory period of increased tariff protection starting in 1983 in response to the 1982-3 recession. These temporary measures peaked in 1984, when tariffs increased uniformly to 35%. Nevertheless, Chile remained strongly committed to free trade: it did not introduce any non-tariff barriers, and tariffs again declined to a 10% ad-valorem level in the 1990s.

The other side of this impressive reduction in the barriers to trade is the systematic increase in the ratio of import penetration[25]. Figure 6.1 plots tariffs against the average import penetration ratio across different manufacturing sectors. The results clearly points to a negative correlation between these two variables. Overall the exposure of the Chilean manufacturing sector to foreign competition, as given by the import penetration ratio, has grown from 25% of the domestic demand in 1979 up to almost 50% of the domestic demand in 2000. In this section we investigate the extent to which this increasing exposure to foreign competition has played any role in total factor productivity growth. We study first the impact of foreign competition on productivity growth by the survivors and second we move to the impact of foreign competition on productivity through the exit of low productivity plants[26].

6.1 Openness, Foreign Competition and Survivors Total Factor Productivity Growth

To estimate the relationship between total factor productivity and foreign competition we follow Nickell (1996) and Disney et.al (2003) and specify the following model:

$$tfp_{ijt} = \beta_1 Z_{jt} + \beta_2 Z_{jt} t + \frac{(\mu - 1)}{\mu} Y_{jt} - \varepsilon_k k_{ijt} + \varphi_i + \lambda_I + \lambda_t + \varepsilon_{ijt} \quad (6.1)$$

which simple says that total factor productivity *level* depends on a the *level* of the variables captured in the vector Z_{jt} and that total factor productivity *growth* depends also on the *level* of the same variables in the vector Z_{jt}. We also add a series of plant, sector and time fixed effects. Following Klette, et al (2000) and Griliches and Mairesse (1998) two additional control variables are the plant's capital stock (k_{ijt}) and sector total output (Y_{jt}). These two variables are included in order to control for the effects of deviations from some of the assumptions used to compute total factor productivity. The plant's capital stock controls for deviations from the assumption of constant returns to scale, while the industry sales variable controls for deviations from the assumption of perfect competition.

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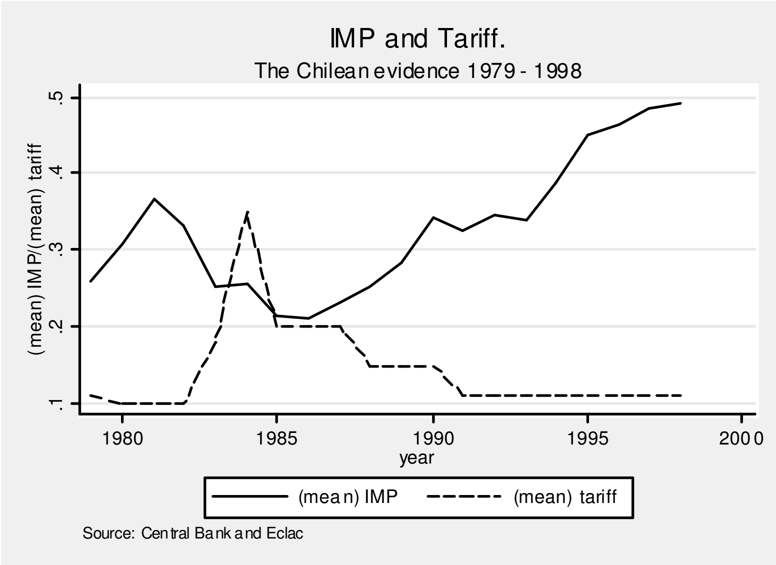
[25] Import penetration is measured as the ratio between imports to imports plus output less exports

[26] Foreign competition could also affect the creation of new plants. However in order to properly evaluate this entry effect we would need the total population of potential entrants something that is rarely available.

Figure 6.1 Imports Penetration and Tariff



The vector Z_{jt} contents two variables related to the competition regime in the sector. The first one refers to the extent of foreign competition and is measured by the ratio of import penetration defined above. The second one refers to the importance of domestic competition and is given by the C_4 sales concentration ratio. Or more formally:

$$Z_{jt} = \left(C_{jt}^{4}, IMP_{jt}\right) \text{ (6.2)}$$

In order to remove for the influence of plant's fixed effects we take first differences in (6.1) and we estimate the following model:

$$\Delta tfp_{ijt} = \beta_1 \Delta Z_{jt\text{-}2} + \beta_2 Z_{jt\text{-}2} + \frac{(\mu - 1)}{\mu} \Delta Y_{jt} - \varepsilon_k \Delta k_{ijt} + \lambda_I + \lambda_t + \Delta\varepsilon_{ijt} \text{ (6.3)}$$

Where two lags of the competition variables have been included in order to deal with endogeneity issues. The results of estimating equation (6.3) are summarised in the Table 6.1. Columns (1) to (4) show the results when using ordinary least squares (OLS) but different sets of control variables. The findings are quite clear: an increase in import penetration reduces total factor productivity levels in the short run (the coefficient on ΔIMP_{jt} is negative and significant) but increases total factor productivity growth (hence levels) in the long run (the coefficient on IMP_{jt} is positive and significant). There is a trade off in operation: the short run costs of an increased exposure to foreign competition are a reduction in productivity levels, this will be more than compensated by an increase in total factor productivity growth over time.

Domestic competition is also important: an increase in the degree of C_4 concentration will boost total factory productivity levels in the short run but it will decline total factor productivity growth in the long run. As a further robustness checks, column (5) estimates equation (6.3) by including plant specific fixed effects; however the results are almost the same.

One additional concern when estimating equation (6.3) is that the estimation sample is formed by surviving plants only (since we estimate in first difference a plant must be present for at least two time periods). This might induce a problem of sample selection bias in the estimated coefficients for the competition variables. To see this we can think that the plant's survival probability is the omitted variable in equation (6.3). This probability should be negatively correlated with competition. In the other hand, competition should be positively correlated with productivity growth. Hence, if there is a positive correlation between productivity growth and survival, the failure in correcting for sample selection will tend to underestimate the true effect of competition on productivity growth. A standard approach to handling the selection issue is to condition (6.3) on an auxiliary equation containing variables that capture the probability of the plant surviving. In our case these variables are size, relative productivity, other plant characteristics such as ownership, legal organization and age plus a series of cohort, region and sector dummies. The results of this correction are shown in column (6) of Table 6.1. The coefficients for the competition variables change in the right direction as if they were affected by a problem of sample selection bias. However, the actual magnitude of the changes is very marginal and the main conclusions hold.

To assess the impact of foreign competition we just plug the coefficients from column (6) in Table 6.1 into equation (6.3) and compute the proportion of total factor productivity growth due to the levels and changes in import penetration. We accumulate these figures for all over the period and we obtain that total factor productivity growth due to the increase in import penetration all over the period was 2.2% of a total of 6%. In other words 30% of plant total factor productivity growth (the within effect) was due to the increase in the foreign competition

Table 6.1 The TFP/foreign competition relation ($\Delta lnTFP$)

	OLS (1)	OLS (2)	OLS (3)	OLS (4)	FE (5)	2-step (6)
ΔIMPjt-2	-0.092	-0.093	-0.092	-0.070	-0.074	-0.092
	[4.51]***	[4.55]***	[4.67]***	[3.59]***	[3.42]***	[0.02]***
ΔCONjt-2	0.094	0.096	0.090	0.090	0.093	0.095
	[3.30]***	[3.37]***	[3.20]***	[3.18]***	[2.98]***	[0.02]***
LIMPjt-2	0.074	0.075	0.066	0.043	0.051	0.073
	[3.89]***	[3.93]***	[3.55]***	[2.29]**	[2.36]**	[0.02]***
LCONjt-2	-0.052	-0.051	-0.052	-0.080	-0.083	-0.050
	[1.89]*	[1.85]*	[1.95]*	[2.97]***	[2.56]**	[0.02]**
ΔK_{jt}			-0.298	-0.300	-0.315	
			[60.12]***	[60.61]***	[58.65]***	
ΔABS_{jt}				0.105	0.102	
				[11.92]***	[10.95]***	
Observations	54581	54581	54581	54581	54581	54581
R-squared	0.050	0.050	0.140	0.150	0.220	
ρ						0.134***

Note: All regressions include time and 3 digit industry dummies. Equation (2) to (6) also controls for the plant specific characteristics such as age, ownership, legal organisation and multiplant firm. Robust t-test. ρ = corr(e1,e2) where e1 is the random error from the regression equation and where u2 is the random error from the probit equation. When ρ≠0, OLS is biased

6.2 Openness, Foreign Competition and Total Factor Productivity Growth due to Exit

The exit of low productivity plants is another important mechanism inducing aggregate total factor productivity growth. In this section we investigate the extent to which an increase in foreign competition will increase the exit rates and hence will increase aggregate productivity growth due to the exit of low efficiency plants. We follow Jenkins (1995) and estimate a discrete time duration model using a logistic specification such as:

$$h_{ijt} = \frac{1}{\left[1+\exp\left(-\theta(t)-\beta' Z_{ijt}\right)\right]} \quad (6.4)$$

where h_{ijt} is the hazard rate and Z is the same vector of competition variables as before. We also use 2 lags to control for endogeneity issues. The baseline hazard function ($\theta(t)$) is non parametric. We also add firm specific control variables. The results of this exercise are shown in Table 6.2

Column (1) in Table 6.2 controls only for the competition variables plus the dummy effects. The results indicate that an increase in foreign competition is positively correlated with exit probability. Column (2) also control for plant specific characteristics: we found that size and relative total factor productivity are negatively correlated with probability of exiting business. However, even controlling for these variables the positive effect of import penetration remains. Column (3) adds additional plant level control variables. We found that a plant owned by a publicly listed firm and a multiplant firm has a higher exit probability once controlling for size and relative productivity. However, the positive sign of the import penetration coefficient remains. Finally, column (4) also controls for sector output growth. This variable was only marginally significant and it did not affect the previous findings.

In order to guess the potential impact of increase foreign competition on aggregate productivity growth we need first to estimate its effects on the exit probability. For doing this we calculate:

$$\Delta P(EXIT_{ijt} = 1) = P(EXIT_{ijt} \mid IMP_{jt}) - P(EXIT_{ij0} \mid IMP_{j0}) \quad (6.5)$$

in every year between 1980 to 2000. We found that the average additional exit due to import penetration is 20% per year over the period. Under the assumptions that: (a) an exiting plant due to increase import competition has the same size as the average exit plant and (b) that that exiting plant has also the same average relative total factory productivity as the average exit plant (-7.2%) we can infer that increased exit due to higher foreign competition contributed 1.4% of total factor productivity growth all over the period, or about 16% of the total net entry effect.

Table 6.2. The Survival/foreign competition relation

Variables	Logit (1)	Logit (2)	Logit (3)	Logit(4)
D_{ummy} 79		-0.021	-0.022	-0.022
		[10.63]***	[11.07]***	[11.17]***
Age		0.001	0.001	0.001
		[0.71]	[0.69]	[0.70]
LSIZE		-0.022	-0.027	-0.027
		[33.29]***	[34.00]***	[33.87]***
TFPrel		-0.018	-0.014	-0.014
		[8.53]***	[6.60]***	[6.52]***
Type			0.022	0.022
			[9.16]***	[9.11]***
FDI			0.000	0.000
			[0.03]	[0.03]
Firm			0.022	0.022
			[6.06]***	[6.04]***
LIMPjt-2	0.071	0.109	0.07	0.069
	[9.34]***	[12.69]***	[9.13]***	[9.04]***
LCONjt-2	-0.069	-0.081	-0.077	-0.073
	[4.95]***	[5.12]***	[5.52]***	[5.19]***
ΔABS_{jt}				-0.006
				[1.63]
Constant	0.108	-0.172	0.149	0.148
	[7.94]***	[19.54]***	[10.51]***	[10.43]***
Observations	75603	75603	75603	75603

Note: All regressions include 3 digit industry and regional dummies..

7 Conclusions

In this paper we have identified the main stylised facts of Chilean manufacturing productivity growth. After introducing the data, the discussion proceeded to measurement of TFP. The main advantages of the index number method used here are its simplicity and the fact that it was not necessary to specify any underlying production technology or to deal with the problems of identification of the underlying econometric relationships. However, these advantages come at some cost, related to the fact that in order for the index to be able to represent the underlying technology well, we need to assume perfect competition in the product and market factors. Finally, the non-parametric nature of the index number approach does not allow controlling for errors of measurement in the variables. Application of index number methods for computing plant-level time-variant TFP, produced some important results.

First, the long-run TFP growth trend for the whole of manufacturing stands at about 1.2% per year, and it is procyclical over the business cycle.

Second, TFP is not a major component of long-run output growth. Indeed, during the peak-to-peak period we can see around 25% of total growth is explained by productivity growth. However, if we look at the period as a whole, the importance of productivity as a source of economic growth declines over time. The explanation for this lies in the asymmetric role of capital accumulation. While the older business cycle was characterised by a very low investment rate in manufacturing that kept capital stocks almost static, the new business cycle that corresponds to the last years in our sample is characterised by a very high level of capital formation (setting records in Chilean economic history). This reduces the importance of productivity as a source of growth in the aggregate, and even makes productivity growth negative during the last part of the time frame. In this case, it seems there is a negative correlation between TFP growth and capital formation, which is in line with the findings from studies of industrialised economies.

Third, there is considerable heterogeneity at the micro-sector level. In some sectors TFP is growing at a rate higher than 3% per year over the period, especially some branches of very scale-intensive sectors, such as iron and steel and beverages, that coexist with more traditional sectors that show some dynamism, such as furniture and textiles. Of the more human-capital intensive sectors the most dynamic is scientific tools. These types of sector coexist with other activities of very low or even negative productivity growth such as tobacco, wood products, oil refining and derivatives.

Fourth, there is a massive heterogeneity in the distribution of TFP. We found differences of more than 100% in productive efficiency between the top and bottom percentiles of productivity distribution. This heterogeneity, which is not peculiar only to the Chilean case, is very persistent over time, even in the context of an industrial sector with almost free trade.

Fifth, given this massive heterogeneity, it is not surprising that net entry plus market share reallocation effects (termed "external restructuring" by Disney *et al.*, 2003) constitute the main driving force underlying TFP growth. Indeed, the combined effect of these two elements represents 57% of TFP growth. Of these two effects the most important is the replacement effect from new highly productive plants replacing less efficient ones. The positive market share reallocations within each specific branch also contribute to TFP growth, reflecting a continuous gain in market importance by the most efficient survivor plants.

Sixth, the contribution of net entry changes over time. Net entry makes a positive contribution to TFP growth in all the sub-periods except the last. This is because the quality of entrants in latter years has greatly deteriorated. This coincides with the phase of greatest capital formation and the increase in the initial scale of the entrants (and potentially their technological complexity). The deterioration in the performance of new plants is also shared by the incumbents.

Seventh, international comparisons show that Chile is not an outlier. Using relatively "comparable" methodologies both for computing TFP and decomposition analysis, we find that Chile (and the other developing countries in the table) has a relatively larger bias towards selection, mainly due to the influence of net entry, while for the developed countries within-plant improvements are more important.

Eight, across a large part of the sample time period *average* efficiency advantages of entrants are due to the presence of high productivity levels at entry. There is no clear evidence that the contribution of net entry is due to wrongly allocated, post-entry learning or growth effects.

Ninth, the above does not mean that *all* the new plants are always better than the incumbents, as the standard vintage model would predict. Some of the new plants also have low productivity levels and in some cases this leads them to exit soon after entry. This is captured both by the shrinking in the productivity spread of the new cohorts as the cohorts age, and the negative correlation between exit and initial productivity in the case of new plants.

Tenth, the transition matrix analysis points to the presence of a very complex industrial dynamics model. The dynamics can be explained only partially by vintage effects: "advantages of birthright" (or fixed effects) and the results of active search and innovation processes also seem to contribute. In other words, plants face a process of productivity erosion over time, and eventually many of these plants fail and exit, but a remarkable fraction are able to re-invent themselves.

Eleventh, increased competition from import penetration has been a major determinant force of aggregate total factor productivity growth. Overall, increased import penetration explains 30% of within plant productivity growth and 16% of the total replacement effect.

If we are to understand the fundamentals of TFP growth and efficiency improvement in an economy such as Chile, it is clear that, in addition to explaining TFP growth trends at sector level, we must incorporate the issue of heterogeneity. With so large differences in TFP among plants within the same sector as found here, it is hard not to question the validity of the assumption of a *representative plant*, and to ignore the importance of the competitive process and selection as key sources of aggregate productivity growth.

Appendix

(A.1) Reliability Analysis and Sample Coverage

One important issue is to what extent the information collected in ENIA covers the total manufacturing sector in Chile. Verifying this is not a trivial task, because we lack additional independent sources of information, as ENIA is the official data set on manufacturing collected by the INE and used by the Central Bank for National Accounts calculations. However, there are two other independent data sets that we can use for comparison, especially in the case of the latter part of the sample period.

The first was built by the Servicio de Impuestos Internos (Tax System Authority) for the years 1994-2000. This data set is not totally independent because the ENIA directory is built on the basis of Tax System information; however, ENIA covers only the population of plants with ten or more workers and omits information from micro plants. Moreover, comparison can be made by taking into account that, while the Tax System information covers firms, ENIA covers plants. We think that the exercise is still valid if we consider that roughly only 10% of the plants come from multi-unit firms. Table A. 1shows the results of this reliability analysis. We find that, during the time period 1994-2000, the number of economically active manufacturing firms[27] grew by 7,000, while the number of plants in ENIA declined by 500, as a consequence of which, global coverage in terms of productive units deteriorates over time, declining from 14% of the population to little more than 10%. The global coverage in terms of sales is remarkably higher, although it also deteriorates over time; it reached nearly 80% in 2000. This imbalance in the representativeness of the survey is a natural consequence of the sampling design, which focuses only on plants with ten or more workers.

[27] We say "economically active" because, as with ENIA, we have not considered those firms with zero sales.

Table A.1
Reliability Comparisons: ENIA vs. Tax System Authority

Year	Plants (1)	Firms (2)	Share (1)/(2)	Sales Shares
1994	4841	35616	13.59	84.02
1995	4901	37014	13.24	89.04
1996	5235	38540	13.58	86.81
1997	4986	37109	13.44	80.40
1998	4572	39365	11.61	81.05
1999	4176	40659	10.27	72.35
2000	4328	42914	10.09	78.23

Source: Tax System Authority

In terms of coverage by sector, the sampling is not proportionally distributed: representation in terms of plants is particularly high in the chemical sectors such as oil derivatives and refining and in non-ferrous metals, branches where sampling proportions are almost 50%. At the same time this participation is very low in glass, furniture and ceramics, with less than 6% in every case. If we look at the sales proportions, coverage across all sectors increases dramatically (Table A.2). We have almost 100% coverage in plastics and non-ferrous metals and also very high levels in non-electrical machinery, foodstuffs, oil refining and wood products. The only sector where sampling proportions are low is tobacco (20%).[28]

[28] Tobacco is also the ENIA sector where the most missing values are found in certain variables and where some of the reported values are clearly inconsistent.

Table A. 2
Reliability Comparisons
by sector: ENIA vs. Tax System Authority (average 1994-2000)

Sector	Plants (1)	Firms (2)	Share (1)/(2)	Sales Shares
Foodstuff	9247	48474	19.08	87.54
Other Food	551	3299	16.70	60.61
Beverages	584	2865	20.38	48.43
Tobacco	16	48	33.33	20.73
Textile	2163	16780	12.89	61.14
Apparel	2041	30314	6.73	47.09
Leather	279	4160	6.71	51.93
Shoes	911	6363	14.32	42.46
Wood Products	2422	14696	16.48	79.57
Furniture	964	17463	5.52	54.27
Pulp & Paper	495	2329	21.25	48.86
Printing	1403	32830	4.27	48.04
Basic Chemicals	414	2946	14.05	62.68
Fine Chemicals	1254	5245	23.91	48.98
Oil Refining	21	51	41.18	89.70
Oil Derivatives	129	279	46.24	80.13
Rubber Products	391	2804	13.94	56.16
Plastics	1525	5095	29.93	99.12
Ceramics	86	1734	4.96	31.14
Glass	113	884	12.78	73.19
Cement	1057	4894	21.60	79.39
Iron & Steel	203	1599	12.70	57.60
Non-Ferrous Metals	321	709	45.28	93.52
Metalworking	3260	35667	9.14	56.53
Non-Electric Machinery	1,428	12705	11.24	85.76
Electric Machinery	428	6962	6.15	25.88
Transport Equipment	749	4090	18.31	48.67
Scientific Instruments	146	1310	11.15	51.68
Other Manufacturing	438	4622	9.48	29.24

Source: Tax System Authority

The second data set that can be used corresponds to the CASEN survey. This is a survey conducted by the Planning Ministry to gather information about poverty and social conditions in the population at large. The survey, with a sample of more than 40,000 households, is conducted every two years. Using the CASEN survey it is possible to know the total size of the workforce in manufacturing and also how the population is distributed across sectors. We have used information from the 1996 survey, because it has activity sector classifications closer to the International Standard Industry Classification (ISIC) used in ENIA.

According to the CASEN survey, the manufacturing workforce in 1996 was over 800,000 (Table A.3). According to ENIA the number was less than 400,000, meaning that coverage is just over 45% of the working population. Some sectors are particularly well covered, for example we have in ENIA 97% of the workforce in iron and steel and 75% in chemicals. The two worst cases are textiles (35%) and wood products (26%).

Thus, the ENIA data set seems to be small from the point of view of the number of plants it covers. However, because the sampling criteria used in the survey included only plants with ten or more employees, there is a strong bias towards the largest plants, and the coverage of the data set in terms of production and workforce is very high. Obviously, because there is an underestimation in the number of small productive units, it is expected that the importance of exit and entry will be also underestimated.

Table A.3
Reliability Comparisons: ENIA vs. CASEN, 1997

	CASEN (1) 1996	%	ENIA (2) 1996	%	(2)/(1) %
Foodstuffs	226375	27.60	120709	31.67	53.32
Textiles & Apparel	167685	20.50	58150	15.26	34.68
Wood & Furniture	137921	16.80	35917	9.42	26.04
Pulp & Paper	61289	7.50	24342	6.39	39.72
Chemicals	60451	7.40	45822	12.02	75.80
Ceramics, Glass & Cement	36807	4.50	15237	4.00	41.40
Iron & Steel	18613	2.30	18129	4.76	97.40
Metalworking	110085	13.40	62813	16.48	57.06
Total	819226	100	381119	100	46.52

Source: Casen Survey, Mideplan

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