Idiosyncratic Productivity Shocks and Plant-Level Heterogeneity[*]

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Abstract

Using plant-level data on Chilean manufacturing firms for the 1980-99 period, we estimate and characterize disaggregate total factor productivity. We show that idiosyncratic productivity shocks are a quantitatively relevant source of the observed heterogeneity in the behavior of plants. Both exit and input demand decisions are correlated with our estimates of plant level productivity. We then use these estimates to study the microeconomic sources of aggregate growth. We decompose productivity dynamics into production reallocation and within plant efficiency changes. We find that both sources of productivity growth have significantly contributed to efficiency gains in Chile during the last two decades. Although reallocation effects are always positive, the magnitude of their contribution is larger during periods of negative or low growth. Within-plant productivity growth contributes positively only during the 1990s, consistently with the existence of a lag between the implementation of major market oriented structural reforms -- mostly undertaken during the late 1970s and early 1980s -- and their complete effect on the economy. Once reforms were consolidated, unbounded within-plants efficiency gains driven by technology adoption and innovation occurred.

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1. Introduction

Increasing availability of micro-level data has allowed the documentation of a widely accepted regularity: for high levels of disaggregation and even within the same sector and period of time, plants are expanding and contracting, entering the market and shutting-down. As a result, a continuous process of creation and destruction of jobs and capital at a highly different pace is observed. These regularities have been documented for developed and developing economies. Evidence for Chile, reported in Camhi, Engel and Micco (1997) and Bergoeing, Hernando and Repetto (2003), is consistent with these findings. [1]

Several factors have been proposed to account for the observed heterogeneity in plant-level outcomes. Some studies stress the role of the uncertainty that surrounds production decisions, resulting from either the development and adoption of new production techniques, or the distribution and marketing of new products. Also, firms experiment with different production processes as they lack full information on the demand conditions and cost effectiveness of alternative technologies. Differences in managerial skills may be another source of plant-level heterogeneity.

The hypothesis of this paper is that the differences in the behavior of plants are explained by plant specific shocks that can be characterized as changes in total factor productivity (TFP). We thus focus on idiosyncratic productivity shocks as a determinant for the observed plant-level heterogeneity. Consistently with profit maximization behavior, plants behave differently, growing or shrinking, creating and destroying jobs and capital, staying or leaving the market, as a response to idiosyncratic shocks.[2]

Using plant-level manufacturing data for Chile during the 1980-1999 period, we estimate and characterize disaggregate TFP. The estimates confirm the hypothesis of productivity heterogeneity at the micro level and show its relevance as a source of the observed behavior of plants. In particular, even within narrowly defined sectors, at any period of time there are wide differences in TFP. These TFP estimates behave according to expected patterns. In general, bigger, older, and more outward oriented plants are more productive. Some of these patterns are strengthened when we control for age, cohort and business cycle effects. Moreover, we find that the TFP estimates are a quantitatively relevant source of the behavior of plant as they correlate significantly with input demands and exit decisions. Specfically, we find that the elasticity of employment to productivity ranges between 0.08 and 0.35. Furthermore, we find evidence consistent with fixed adjustment costs to investment as the probability of investing is 15.4 percentage points larger for plants that experienced productivity shocks in the highest quartile of the TFP distribution relative to the lowest quartile. Finally, we find that an increase of one standard

[1] See, for the United States, Davis, Haltiwanger, and Schuh (1996) and Doms and Dunne (1998), and for the OECD see Ahn (2001).

[2] Salter (1966) provides comprehensive evidence of heterogeneity in 28 industries in the United States during the 1924-1950 period. He suggests that the observed heterogeneity in output, employment, prices, costs and earnings across plants may be the result of uneven technical change among industries.

deviation in productivity reduces on average the shut down probability by 0.76 percentage points.

Finally, we study the microeconomic sources of aggregate growth by establishing a link between plant-level behavior and aggregate productivity dynamics. The recent Chilean experience provides an interesting case to study the sources of growth. During the second half of the 1970s and the beginning of the 1980s, several market-oriented reforms were implemented in Chile. Most sectors in the economy were homogeneously exposed to international trade, companies were privatized, and distortions were eliminated. These economic transformations facilitate the adoption of more advanced technologies and more efficient production processes, and generated market share reallocations and sectoral efficiency gains. Previous studies, however, have only partially analyzed the effect of these reforms on aggregate growth: they either exclusively look at aggregate data or they focus on periods of time too short to allow these reforms to fully affect the economy. Additionally, during the early 1980s the Chilean economy experienced, as most countries in Latin America, a deep fall in economic activity, with GDP decreasing almost 20 % during the 1982-83 period. Only a decade later the economy recovered its pre-crisis trend value in GDP per capita.[3] Then, in 1998, after almost 15 years of sustained and stable growth, economic activity stagnated.

Thus the plant-level total factor productivities we estimate in this paper comprise 20 years characterized by several relevant shocks, providing a rich source of information that allows us to better understand the link between plant-level behavior and aggregate dynamics. We find that both within plant efficiency changes and reallocation effects have been relevant for aggregate TFP growth. Over all the sample period reallocation effects are positive, indicating that resources are shifted towards more efficient plants. Within-plant TFP growth positively correlates with total TFP growth over most of the period. Although it is positive on average for the full period, during many subperiods it contributed negatively to total productivity growth. The relative importance of these sources of productivity gains has varied over time.

The paper is organized as follows. The next section of the paper describes the estimation algorithm and the theoretical framework of firm exit behavior that supports it. In Section 3 we present the data used in the estimations, we characterize plant-level TFP, and we quantify the relevance of idiosyncratic productivity shocks as a source of the observed heterogeneity in plant outcomes. Section 4 uses the estimates of plant-level TFP to study the contribution of reallocation and within plant efficiency changes into aggregate productivity dynamics. The final section concludes.

[3] See Bergoeing et al. (2002).

2. A Theory and Estimation Procedure of Productivity Dynamics

As reported by Camhi, Engel and Micco (1997) and Bergoeing, Hernando, and Repetto (2003), and consistent with the international evidence, Chilean manufacturing data show substantial heterogeneity at the plant level. Even within narrowly defined sectors, at any period of time the Chilean economy is characterized by large and persistent differences in factor-input usage and output across plants. Idiosyncratic productivity shocks are one possible explanation for this heterogeneous behavior. In this section we describe a theory of plant exit and input demand based on plant specific productivity shocks, and the algorithm to estimate plant-level TFP based on this theory, developed by Olley and Pakes (1996).

A Model of Plant Heterogeneity and Exit Decisions

Assume the economy is populated by a continuum of heterogeneous firms, each one with its own level of productivity.[4] In every period, given factor prices and the market structure, the manager of each firm decides whether to quit production and exit, or to stay in business. The exit decision is irreversible. The manager's decisions are made after facing an idiosyncratic productivity shock that is a random draw from an exogenous Markov process. If the firm continues in operation, the manager purchases variable factors and chooses a level of investment. If she decides to exit, the plant is worth a sell-off value of Ψ. Exit decisions are based on profit maximization so as to maximize expected discounted net cash flows. The firm's problem thus is

$$V_t(\omega_t, k_t) = \max\{\Psi, \sup_{i_t \geq 0} \pi_t(\omega_t, k_t) - c(i_t) + \beta E_t V_{t+1}(\omega_{t+1}, k_{t+1})\}$$

where $c(i_t)$ represents the cost of investment, β the firm's discount factor, E_t the expectation operator conditional on all information known at time *t*, and V_t the value function at period t. The profit function of the firm is represented by $\pi_t(\omega_t, k_t)$, which depends on the current value of the state variables, capital (k_t) and productivity (ω_t). The function is indexed by time to account for changing market structures and factor and output prices. The law of motion for capital is given by

$$k_{t+1} = (1-\delta)k_t + i_t$$

where i_t is current period's gross investment.

Conditional on capital stock, k_t, equilibrium exit decisions are given by a cut-off level of productivity $\omega^*_t(k_t)$, as shown by Ericson and Pakes (1995). If $\omega_t \geq \omega^*_t(k_t)$, the firm stays in business, and if $\omega_t < \omega^*_t(k_t)$, the firm exits. This cut-off is decreasing in k_t if the difference between the expected discount value of profits and the sell-off value depends

[4] In this paper we refer to firms and plants as equivalent economic units, although our data set collects information on plants and not on firms.

positively on capital; i.e. larger firms lose more if they choose to quit. In other words, a larger capital stock allows firms to stay in business even if current productivity is relatively low. Finally, if the plants stays, the investment demand is given by $i_t = i_t(\omega_t, k_t)$. Pakes (1994) shows that for any capital stock, if investment is strictly positive, the investment function i_t is strictly increasing in ω_t. The monotonicity of the cut-off and investment demand functions are key ingredients for the OP algorithm that is outlined in the next subsection, as they will be used as proxy for the unobserved productivity shocks.

The Olley-Pakes Estimation Strategy

The first step in constructing series of TFP is estimating a production function. Within this theoretical framework, the empirical estimation of production functions is problematic because productivity, a state variable in the firm's decision problem, is not observed by the econometrician. Two biases in OLS estimation of the production functions are introduced. First, there is a simultaneity problem, as factor demands are correlated with the unobserved productivity term. Specifically, if firms with higher productivity are more likely to purchase inputs, then OLS estimates of the corresponding coefficients are biased upwards. Second, there is a selection problem since conditional on survival the econometrician only observes plants with productivity greater than the cut-off. The expectation of productivity will depend negatively on capital since firms with a larger capital stock can afford to survive with a lower productivity level. Thus, the capital coefficients are biased downwards.

Fixed effects regressions do not solve the simultaneity problem since they require the productivity term to be constant over time.[5] Given the length of the period considered and since structural reforms were undertaken during the period studied, it is highly unlikely that productivity remained constant. As a matter of fact, the results in Pavcnik (2002) for the 1979-86 period suggest that fixed effects regressions do not fully control for the endogeneity problem, and thus that plant-level productivity is not constant over time. Similarly, balancing the panel of firms does not solve the selection problem, since firms that remain in the panel are firms that survived. To circumvent these problems we use a general estimation procedure proposed by Olley and Pakes (OP) and modified by Levinsohn and Petrin (LP).[6]

Let the production function of firm *i* at time *t* be

$$y_{it} = \beta_0 + \beta_s l^s{}_{it} + \beta_u l^u{}_{it} + \beta_k k_{it} + \omega_{it} + \mu_{it}$$

where y_{it} is log value added, $l^s{}_{it}$ is the log of skilled labor input, $l^u{}_{it}$ is the log of unskilled labor input, k_{it} is the log of the plant's capital stock, ω_{it} is the log of plant-specific productivity, and μ_{it} is a mean zero error that accounts for measurement error and for unexpected productivity shocks that do not affect the choice of inputs.

[5] See Griliches and Mairesse (1995) for a thorough analysis of the simultaneity problem.
[6] See Olley and Pakes (1996) and Levinsohn and Petrin (1999).

The estimation procedure developed by OP is built in three steps. The procedure relies on the assumption that next period's productivity depends on current period's productivity, which in turn can be written in terms of observables. In the first step, a consistent estimate of the coefficients on variable inputs, skilled and unskilled labor, is obtained. This is achieved by controlling for the unobserved shock by inverting the investment function and approximating ω_{it} by a polynomial expansion in investment and capital. The second step consists of the estimation of the exit probability of any given plant using polynomial expansions in capital and investment. This estimated probability is used in the third step to control for the cut-off, and thus to correct for the selection problem. The final step identifies the coefficient on capital after substituting the parameters estimated in the previous steps into the production function.

Several assumptions of the OP procedure deserve further attention. First, the investment demand function must be inverted in order to recover productivity as a function of observables. This is technically possible only if investment is strictly positive. However, a large number of plants in our data set do not invest due, perhaps, to the presence of fixed adjustment costs to investment. To use the OP algorithm these observations must be excluded since investment is no longer useful in controlling for the correlation between productivity and variable inputs. In our data set, the procedure thus requires the exclusion of about 40% of the available observations. Nevertheless, Levinsohn and Petrin (1999) have proposed to replace investment for intermediate inputs as a control for unobservable productivity shocks. If intermediate inputs can be adjusted without cost and if they respond to productivity shocks, they can be used instead of investment. We follow LP and use electricity as a control. Almost all our plant/year observations have positive levels of electricity. Furthermore, electricity cannot be stored by firms, so its current demand must be correlated with current productivity. Nevertheless, it is worth emphasizing that the use of electricity as a proxy for productivity requires the use of value added as the measure of output.[7] Since value added does not include the contribution of materials, intermediate inputs such as electricity and energy can then be used as proxies for productivity. However, if materials are mismeasured, part of the contribution of intermediate inputs remains in value added. If so, the method yields biased estimates of all coefficients, as the measurement error and the productivity correction term are correlated.

Second, Olley and Pakes (1995) have shown that kernel estimators of g provide consistent and asymptotically normal estimators of the production function coefficients. No proof is available for series estimators of g. In this paper we use polynomial expansions, so we provide bootstrap standard errors to account for the fact that we do not have a well-defined limiting distribution of the estimators.

Third, the theoretical model assumes, as it is standard in the literature, that period t investment becomes available for production with a lag. So, if firms observe the productivity shock before they choose a level of investment, then current period's capital is not correlated directly with productivity. Previous papers using Chilean manufacturing data have used the capital stock series constructed by Liu (1993). This series assumes that

[7] For a discussion on the meaning of the production function at the firm level using value added, see Basu and Fernald (1995).

investment becomes productive immediately, so current period's capital stock is effectively correlated with the productivity shock. To correct for this problem, LP change the assumptions about the timing of firm's actions so investment in *t+1* can be used as a proxy of productivity in *t*. We take the alternative route: we redefined capital so as to make it consistent with OP's modeling assumptions, and reconstructed the series.

Fourth, the unit of analysis of the theoretical model is the firm. However, we observe plants and not firms in our data set. In other words, we are unable to distinguish single-plant firms from multi-plant firms.[8]

Finally, the algorithm assumes that the only state variable that affects the firm's decisions, but that is unobserved by the econometrician, is the productivity shock. Without this assumption, the investment demand cannot be inverted in order to write productivity as a function of observables. If investment depends on other unobservables, the one-to-one correspondence between productivity and investment, holding fixed the capital stock, no longer holds. Using a Montecarlo experiment, Syverson (2001) has shown that if the choice of inputs depends upon the unobserved expectation of variables such as the state of demand or input prices, OP's methodology yields biased estimates of the coefficients of the production function. To estimate these parameters consistently, instrumental variables are needed. Unfortunately, it is a difficult task to find valid instruments that vary across firms and over time. Nevertheless, the period of analysis is characterized by free trade with production sectors homogeneously exposed to foreign competition. Thus, there at least should be no markup shocks to instrument for.

3. The Dynamics of Productivity in Chile

In this section we characterize the estimates of TFP at the plant level. We use these measures to describe the evolution of productivity over time and across groups of plants controlling for several plant characteristics, such as age, size, and openness. The estimates are consistent with the hypothesis of productivity heterogeneity at the micro level. Moreover, they turn out to be a quantitatively relevant source of the observed heterogeneity in plant dynamics as they are significantly correlated with both, exit and input demands decisions.

The Data

The data in this study come from the *Encuesta Nacional Industrial Anual* (ENIA), an annual survey of manufacturing conducted by the Chilean statistics agency, the *Instituto Nacional de Estadísticas* (INE). The ENIA covers all manufacturing plants that employ at least ten individuals. Thus, it includes all newly created and continuing plants with ten or more employees, and it excludes plants that ceased activities or reduced their hiring below the survey's threshold. The ENIA represents about 50% of total manufacturing

[8] According to Central Bank statisticians, about 3.5% of plants belong to a multi-plant firm in our data set.

employment.[9] It collects detailed information on plant characteristics, such as manufacturing subsector at the 4-digit ISIC level, sales, employment, investment, intermediate inputs and location. The available data cover the 1980-1999 period.

The treatment of entry and exit is somewhat complicated by the fact that plants falling below the minimum employment boundary do not appear in the survey. Thus a plant interviewed in any given year, but that fails to enter the sample in the following year might not represent an exit. Similarly, a plant appearing for the first time in any given year does not necessarily correspond to an entry, as it might represent a growing plant that surpasses the ten people boundary. To reduce the extent of spurious identification of plant entry and exit, we artificially raised the sample threshold to 15 employees, following the strategy in Micco (1995).[10]

We limited the analysis to eight 3-digit subsectors: food products (311), beverages (313), textiles (321), wood products (331), paper products (341), printing and publishing (342), chemicals products (352), and metal products (381). We excluded the other sub-sectors because they are either small, with few observations and/or are organized in a manner inconsistent with the underlying behavioral model. For instance, we excluded petroleum and refining, and tobacco industries, because these sectors are organized as monopolies, and produce with very few plants. Furthermore, petroleum and refining are mostly state-owned. We also excluded sector 39 (manufactures not elsewhere classified) because of its natural heterogeneity.[11]

Production Function Estimates

The model was estimated using a third degree polynomial expansion in the first two steps of the algorithm, and a fourth order polynomial in the last step. The proxy for productivity in the first stage and for the cut off in the second stage were fully interacted with a set of dummy variables to allow the functions to vary over time. We used dummies for the periods 1980-81 (boom), 1982-83 (recession), 1984-89 (main structural reforms and recovery), 1990-1997 (rapid growth), and 1998-1999 (slowdown). We also included these time dummies in the production function, as they turned out to be significant, indicating the existence of aggregate productivity shocks.

Table 1 presents the estimated elasticities of unskilled and skilled labor and of capital using different samples and methods. The left hand side panel of the table reports the estimates of the coefficients using a balanced panel based on plants that did not enter or leave the market during the sample period, whereas the right hand side panel uses the full sample. We present the results using seven different specifications: OLS and fixed effects with both samples, the OP algorithm on all available observations, the OP method

[9] Industrial employment represented roughly 16% of total Chilean employment in 1999.

[10] We also excluded plants that report either no employment or no blue-collar workers, and plants that report zero wages, no production days, zero gross production value, negative value added, gross production value lower then value added, exports that are larger than total sales, or no ISIC code.

[11] The subsectors used in this study account for 60.1 % of total value added in the ENIA, once we exclude copper industries that are classified as mining in National Accounts.

restricting the sample to firms with strictly positive investment, and the LP extension with electricity as a proxy for productivity.[12]

The reported elasticities exhibit wide variation across sectors. No matter which sample or method we use, we find that all coefficients are precisely estimated. In all cases the coefficients add up to a figure quite similar to one, indicating constants returns to scale.[13] If we only consider the LP estimates (which we will later use to analyze the behavior of productivity at the plant level), the degree of returns to scale vary from 0.88 to 1.16. The lowest elasticities of labor are in the printing and publishing sector, with elasticities close to 0.3, whereas the largest elasticities correspond to the beverages sector (with point elasticities of 0.51 and 0.46 for unskilled and skilled labor, respectively.) The coefficient on capital varies between 0.16 (papers) and 0.36 (chemicals).

Pavcnik (2002), using data from the ENIA, obtains elasticities that are much lower than those presented here. Unfortunately, her results are not directly comparable to ours, as she uses a much shorter data set (up to 1986 only), and as she aggregates sectors at a two digit level. Moreover, she estimates production functions for gross production and not for value added, and hence includes materials as an input. Although gross production -- and not value added -- is the right concept at the disaggregate level, we chose to estimate production functions for value added in order to use electricity as a proxy.[14] The use of gross output requires the direct inclusion of materials as inputs, and hence they cannot be used as a proxy for productivity. Nevertheless, although we get different point estimates, Levinsohn and Petrin (1999) obtain coefficients of the same order of magnitude as we do. They use the same subsample of the ENIA that Pavcnik uses, and find increasing returns in all the industries considered. Since we use the same methodology and proxies as LP, the differences in coefficients must be due to the samples used and the timing assumption on capital dynamics.

The omission of productivity in OLS estimations should bias upwards the coefficients of inputs, as unobserved productivity is positively correlated with factor demands. This effect should be larger for factors that are easier to adjust; i.e. skilled and unskilled labor. Furthermore, the bias should be even smaller for capital given our assumption that investment becomes productive with a lag. Fixed effects estimations remove this bias only if productivity is constant over time. We believe it is unlikely that plant level TFP has remained constant over our period of analysis, which is not only long -20 years-, but also characterized by major structural reforms. The direction of the bias on the capital coefficient is ambiguous if one conditions the sample on survival. Since firms with larger stocks of capital can stay in business even with low productivity shocks, there should be a negative correlation between the capital coefficient and the error term. Finally,

[12] We excluded plants that demanded no electricity. A very small fraction of observations had to be eliminated (about 1.5% of them.) Some plants generate and sell electricity. Our measure of electricity is electricity consumed plus electricity generated minus electricity sold.

[13] The existence of constant returns to scale is consistent with the level of openness displayed by the Chilean economy during the period under analysis. It also reflects the fact that we excluded sub-sectors organized as monopolies, such as petroleum and tobacco. Furthermore, it implies that we do not need to control for markup shocks that would invalidate the OP estimating procedure. See Syverson (2001).

[14] See Basu and Fernald (1995) for a discussion on production functions at different levels of aggregation.

the analysis of these biases is further complicated by the fact that labor and capital are correlated with each other.

The OLS estimates of the first column include all these biases. Fixed effects coefficients tend to be much lower than the OLS elasticities. This is consistent with the fact that these estimates remove most of the variation within a firm that is not intertemporal, thus increasing the importance of errors in measurement. Furthermore, the degree of returns to scale is smaller than one in all industries. Including plants that eventually exit from the sample, not only increases significantly the samples available for estimation, but also helps remove the selection bias.

Moving from the full sample OLS to any of the OP type methodologies changes the estimated coefficients in a manner consistent with the theoretical biases. In all cases the labor elasticities are smaller than in OLS estimations. In some cases, the coefficient on capital falls and in others it rises. In most sectors the elasticities of capital change significantly once we move from the OLS procedures to the OP methodology. There are also large changes when we compare the basic OP specification and its two modifications. Removing all plant observations with zero or negative investment changes significantly the estimated coefficients, especially those of capital.[15] In most sectors the coefficient of capital rises, whereas the coefficients of labor fall.

Summing up, our results indicate that in most sectors the correction for simultaneity and survival do change significantly the estimated coefficients. Furthermore, the direction of these changes is consistent with the removal of the expected biases. Therefore, our results confirm that production function estimates based on standard methods are flawed.

Characterizing Plant-level Productivity

Since estimates of plant-level TFP are usually not available, it is common to use average labor productivity to study the connection between efficiency and the behavior of plants. TFP is, however, the right concept to understand this connection. Labor productivity is endogenous to TFP. Moreover, its evolution is determined not only by changes in multi-factor efficiency but also by the reallocation of inputs. The separate understanding of each of these sources of output per capita growth is quite relevant. For instance, while the former is unbounded and accounts for long-run growth, the latter is bounded by the efficient allocation of resources and correlates with the business cycle. Thus, a full characterization of aggregate efficiency allows a comprehensive understanding of long and short run growth.[16]

Next, we characterize the dynamics over time and across different groups of plants of our estimates of TFP.

[15] It also reduces the sample sizes to about a half.
[16] Our estimates of TFP are significantly and positively correlated with average labor productivity in seven out of eight sectors. The correlations range from 0.13 in paper products to 0.55 in beverages.

Let ϖ_{it} represent the estimated of the level of TFP of plant *i* at time period *t*, using the production coefficients previously estimated with the LP version of the algorithm. That is,

$$\overline{\omega}_{it} = \exp(y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_s l_{it}^s - \hat{\beta}_u l_{it}^u)$$

Figure 1 displays the full dynamics of weighted average productivity at the industry level.[17] All series are normalized to 100 in 1980. Although productivity fluctuates largely over time, 7 out of the 8 sectors display an upward trend, indicating that, on average, manufacturing sectors have become more productive in Chile over the period of analysis -- the exception being beverages. In other words, mean productivity growth is positive reflecting that, over time, industries are growing faster than inputs.

Our estimates of TFP show that there are wide differences in efficiency levels, even within a sector and a year. Table 2 provides evidence of such heterogeneity. It shows the ratio of productivity for plants in the ninetieth percentile of the productivity distribution relative to the productivity of plants in the tenth percentile. These ratios show large differences, up to 15 times in some sectors and years. On average, during the 20 years considered, all sector have ratios higher than five, with food products and beverages having ratios higher than nine. These large differences in productivity are one likely explanation for the heterogeneity in exit and input usage decisions observed in the Chilean economy at the plant level.

This dispersion in productivity could be due to measurement problems resulting from statistical errors, differences in input and output qualities across plants within the same sector, or utilization rates. Two reasons provide support for our finding, however. First, our estimates are consistent with the international evidence. Plant level data from both developed and developing economies, where measurement errors are likely to vary, show similar patterns of dispersion.[18] Second, our productivity estimates correlate with other variables in manners consistent with our theoretical priors. In what follows we provide such evidence, describing the evolution of productivity over time and across groups of plants while controlling for plant characteristics, such as age, size, and openness.

The theoretical literature emphasizes several variables as determinants of plant-level TFP. For instance, a number of models with heterogeneous plants relate plant level TFP to plant's age. Jovanovic (1982) assumes that firms are endowed by a cost function that is revealed slowly over time through production activity. Ericson and Pakes (1995) develop a model of learning, in which firms can explore and develop processes that make them more efficient. These hypotheses, and the fact that inefficient firms tend to exit the market, imply that older plants should be more productive than younger ones. Another determinant of the observed patterns in plant-level productivity may be size, as different degrees of economies of scale should induce different efficient scales of production. Finally, specific policies

[17] Plant TFP has been weighted by its contribution to total sectoral value added in any given year.
[18] See Bartelsman and Doms (2000).

should also be relevant as, for instance, they expose plants to different degrees of competition.

Our estimates of plant-level efficiency show mixed patterns. Some sectors display dynamics consistent with our theoretical priors. Others do not, however. For instance, the relationship between size and productivity is mixed. In general, sectors display a positive relationship when size is measured by sales, but this correlation is much weaker when size is measured by the number of employees. Still, these results suggest that economies of scale may be relevant in understanding productivity. They may also reflect reverse causality, as more efficient plants represent a larger share of market sales, and more productive plants tend to demand more labor.

The correlation between age and productivity is also mixed. For instance, in five sectors 10 years-old plants are less productive than startups.[19] These simple correlations, however, confound cohort, age and time effects. Age effects capture the life-cycle of plant level productivity. For instance, if there are learning-by-doing effects, then plants become more productive as they age. Selection effects may also account for an increasing age profile of plant level TFP, as the less productive plants shutdown at earlier ages. However, if different vintages of plants had access to different technologies when they were born, and if the technology frontier continually improves, then older plants -- those born earlier -- display a lower average TFP level. Thus plants in the sample observed at age 20 were born long before those we observe at younger ages and so have on average lower lifetime TFP. Ignoring these birth-year effects leads to a negative bias in the estimate of the slope of the age profile. Finally, year specific effects, such as the stage of the business cycle, may affect average TFP of plants in each year, as aggregate shocks account for a share of individual uncertainty. If certain plants are observed only in the downside of the business cycle, we would then incorrectly assign them a negative age effect.

To control for these different effects, we decompose TFP into age, cohort and time effects.[20] We follow Deaton and Paxson (1994) and attribute growth in TFP to cohort and age effects, and cyclical fluctuations to year effects.[21] As in Deaton and Paxson we normalize the effects such that year effects average to zero over the long run.

The first panel of Figure 2 displays average TFP for four cohorts observed over the 1980-1999 period. The older cohort is composed of plants that entered the market between 1980 and 1984. The other three cohorts are formed by plants that were established between 1985 and 1989, 1990 and 1994, and 1995 and 1999. Each line in the figure tracks average TFP of plants in each cohort over the sample period. That is, the first point in the top line shows average TFP of the youngest cohort in 1995. The second point shows average TFP for this same group in 1996, and so on. The figure shows that there are separate cohort and age effects in plant level TFP. In most cases, at any given age, the lines for younger cohorts are above the lines for older cohorts. For instance, at age three the youngest cohort displays

[19] We only consider plants whose age is actually observed in the sample, namely, plants born within the sample period.
[20] We do not analyze the data at a sectoral level to avoid small sample problems.
[21] Deaton and Paxson (1994) studies the life-cycle profiles of household income.

a level of productivity that is about 60% higher than that of the oldest cohort. This difference reflects the effects of technical progress on different vintages of plants. There is also an upward sloping life-cycle profile, most evident for the cohorts observed for a longer time period. Finally, the age profile of all cohorts is downward sloping during the final years of our sample, possibly reflecting that this has been a period of slow growth in Chile.

The next three panels of Figure 2 show the decomposition into age, cohort and year effects. The estimated cohort effects are declining with age. In other words, plants born later have access to better technologies, and thus display higher average TFP.[22] Age effects are flat until age eight, to then become generally upward sloping until age nineteen when productivity drops again to the level attained before age eight. This initial period of low productivity growth is consistent with selection effects that lead the least productive plants to leave the market at young ages. The rest of the life-cycle profile is also consistent with learning effects. Finally, the drop is productivity by the end of the second decade may reflect the completion of the life cycle of plants, as the evidence shows for plants in the United States.[23] Year effects follow the pattern of the Chilean business cycle. The effects fall dramatically between 1981 and 1982, and then fluctuate until the early 1990s. Then they rise as the economy grows much faster, to finally fall after 1995. Finally, our results show that TFP is driven mostly by age and cohort effects, as cyclical fluctuations account for a small share of overall productivity.

Finally, several studies have argued that trade has been key to account for the sustained period of growth the Chilean economy experienced since the mid 1980s.[24] Table 3 shows the average level of plant-level productivity according to the degree of outward orientation, measured as the ratio of exports to sales. In six sectors, plants that export are more productive than plants that do not, the exception being beverages and paper products. Both of these sectors, however, do display the highest productivity level when exports are larger than 50% of their sales. In general, nevertheless, there is no monotonic relationship between the percent of sales that is placed abroad and productivity. For instance, whereas in beverages the productivity of plants that export more than half their sales is twice that of plants that export 5-10% of their sales, in food products the corresponding ratio is less than a half. Again, these associations do not establish causality: plants that export may do so precisely because they are more efficient, as suggested by Roberts and Tybout (1997).

TFP and Heterogeneous Plant Dynamics

Next, we show that the estimated differences in plant-level TFP are a quantitatively relevant source of the observed heterogeneity in the behavior of plants.

We start by inquiring whether the exit behavior of plants is associated to their efficiency levels. Table 4 compares the mean productivity levels of startups and shutdowns

[22] Jensen, McGuckin, and Stiroch (2001) find that the evolution of productivity in U.S. manufacturing plants from 1963 to 1992 is significantly determined by a “vintage effect” associated with the higher productivity of recent cohorts of new plants relative to earlier cohorts of new plants.
[23] See Bartelsmand and Doms (2000).
[24] For instance, see Pavcnik (2002).

to the mean productivity of continuing plants. On average, plants that shut down have lower productivity than incumbents in the beverages, wearing apparel, paper products, and printing and publishing industries. In the food, textiles, wood, chemical, and metal products sectors, exiting plants display higher productivity than the average continuing plant. At a first sight, this result seems counterintuitive. However, these figures do not control for other relevant factors, such as the capital stock, that are correlated with exit behavior and productivity. Moreover, these figures look only at means, and not at the full distribution of TFP.

To better understand the differences in the productivity of incumbent plants, shutdowns and startups, we constructed the cumulative distribution of productivity for these three groups of plants. Figure 3 shows these distribution functions for the full sample. No matter the level of productivity, the distribution of shutdowns is to the left of the distribution of productivity of continuing plants. In other words, the probability of exceeding any given level of productivity is higher among continuing plants than shutdowns, and thus the first distribution first order stochastically dominates the second distribution. This pattern is also found at the 3-digit aggregation level in most cases. In Table 5 we provide the p-values associated to tests of first order stochastic dominance that compare the TFP distribution of incumbents and shutdowns (Barrett and Donalds, 2003). In all cases but one (chemical products), the tests strongly reject the null of equal distributions in favor of the alternative that the distribution of incumbents dominates the distribution of deaths.

To formally investigate the relationship between exit and efficiency, Table 6 reports the results of probit regressions that explain deaths as a function of the level of productivity and capital, the latter to control for size. We regress the probability of shutting down during the next five years on plant-level productivity. As expected, all sectors but one show a negative coefficient, five of which are statistically significant. Thus, in general more productive and larger plants have a higher survival rate during a five year horizon. However, the magnitudes of the effects are in general not large, as one standard deviation in productivity reduces the shut down probability by 0.76 percentage points for the whole sample. Perhaps, these effects are small because plants in all sectors already have on average a probability of survival of 0.90. Beverages and textiles are the exceptions, with increases in the probability of survival of 18 and 8.7 percentage points respectively.[25]

Next, we study the connection between plant TFP and factor demands. According to the theoretical framework, both labor and capital demand should be increasing in productivity.[26] OLS estimations of the log of labor and the log of the stock of capital as a function of the log of productivity are reported in Table 7 and Table 8, respectively. The results are consistent with our theory as, in general, input demands show a positive productivity elasticity. Furthermore, if we include employment as a regressor for capital

[25] The results are not qualitatively modified if ones regresses the probability of death with the log of productivity and the log of capital. Moreover, probit regressions looking at the probability of death during a one year horizon produce similar results although of smaller magnitude. In this case, the probability of survival for the whole sample increases 0.36 percentage points when productivity increases one standard deviation.

[26] The autocorrelation of TFP in our full database, controlling for year and sector effects, is 0.594.

demand, and capital stock as a regressor for employment demand, to control for size, all coefficients are positive, as expected.

Plant-level employment displays positive and significant coefficients in all sectors. The estimated elasticities are large, ranging between 0.08 an 0.35. Capital, however, although it has a positive and significant elasticity for the whole sample, shows either no significant or a negative elasticity in most sectors. The low correlation between the capital stock and productivity exhibited in these sectors is consistent with evidence of lumpy investment found in our data.[27] If the demand for capital faces non convex adjustments costs, the correlation between current capital decisions and current productivity debilitates. Moreover, our estimates of productivity provide support for the observed lumpiness of investment. Table 9 reports probit regressions for the probability of investing and a set of dummies capturing one-year lagged plant TFP quartiles, from lowest to highest. The coefficients represent the change in the probability of investing when moving from one quartile to the next, relative to the lowest quartile. For instance, the overall effect of moving from the first to the second quartile in the TFP distribution is to increase the probability of investing in 9.7 percentage points. Moving further up the distribution, this probability increases in 3.4 and 2.3 extra percentage points. These are large effects. This pattern holds in general across sectors; that is, the probability of investing and productivity are more positively correlated the larger is the size of the productivity shock. This evidence suggests thatfixed adjustment costs are relevant.[28]

Thus, the estimated correlations between TFP and the behavior of plant-level employment and capital stock provide empirical support for idiosyncratic productivity shocks as a source of observed heterogeneity in the outcome of plants.

4. The micro sources of aggregate productivity growth in Chile

In this section we use our estimates of plant-level TFP to study the microeconomic sources of aggregate growth in Chile during the last two decades. We do so by disentangling aggregate productivity dynamics into two processes: first, the changes in efficiency within firms; second, the reallocation arising from the expansion and contraction of continuing plants as well as from the entry and exit of plants.

The recent Chilean experience provides a rich setting to investigate these sources of growth. During the second half of the 1970s and the early 1980s, Chile carried out several market oriented policies. Most distortions on prices and quantities were eliminated and producers were forced to compete in foreign markets. Overall, these reforms provided an environment that favored efficiency, both through the displacement of resources from less to more efficient producers and from the generalized adoption and innovation of better technologies and production processes. The study of plant-level productivity dynamics allows a complete understanding of the sources of aggregate growth. Most studies that look at the effect of market reforms on growth in Chile have only partially analyzed the current

[27] Considering the full sample, at any moment in time 40% of plants report zero investment.
[28] See Cooper and Haltiwanger (2000).

available evidence. They have missed the effect from reallocation by concentrating exclusively on aggregate data, or they have not captured the complete dynamics resulting from reforms by focusing on a period of time too short to allow these policies to fully affect the economy. Moreover, during the two decades, Chile has experienced both deep depressions and periods of sustained and stable growth.

A separate understanding of both sources of aggregate productivity dynamics is relevant as they implications differ substantially. For instance, while within-plants efficiency increases are unbounded and account for long-run growth, productivity gains from reallocation are bounded by the efficient allocation of resources and correlate with the business cycle.

We follow Foster, Haltiwanger, and Krizan (1998) by decomposing productivity growth into five elements: (i) a within-plant effect, given by productivity growth weighted by initial output shares; (ii) a between-plant effect, that captures the gains in aggregate productivity coming from the expanding market share of high productivity plants relative to the initial aggregate productivity level; (iii) a cross effect reflecting gains in productivity from high-productivity growth plants' expanding shares or from low-productivity growth plants' shrinking shares; (iv) an entry effect which is the sum of the differences between each entering plant's productivity and initial aggregate productivity, weighted by its market share; and (v) an exit effect given by the sum of the differences between each exiting plant's productivity and initial aggregate productivity, weighted by its market share.[29] The decomposition is given by:

$$\begin{aligned}\Delta P_t \quad = \quad & \sum_{i\in C}\theta_{it-k}\Delta p_{it} + \sum_{i\in C}\Delta\theta_{it}(p_{it-k} - P_{t-k}) + \sum_{i\in C}\Delta\theta_{it}\Delta p_{it} \\ & + \sum_{i\in N}\theta_{it}(p_{it} - P_{t-k}) - \sum_{i\in X}\theta_{it-k}(p_{it-k} - P_{t-k})\end{aligned}$$

where Δ refers to changes over the k-year interval between the first year ($t - k$) and the last year (t); θ_{it} is the share of plant's i value added in sectoral value added at time t; C, N, and X are sets of continuing, entering, and exiting plants, respectively; and P_{t-k} is the aggregate productivity level of the sector as of the first year ($t - k$). Thus, new plants contribute positively to productivity growth when they have higher productivity than the initial industry average. Exiters do so when they have lower productivity than the initial industry average. The within effect reflects the contribution of increases in productivity in continuing plants given their initial shares. The between effect reflects the contribution of share changes under the given initial productivity level. Finally, the cross-effect term corresponds to the contribution of continuing plants through changes in market shares of plants with increasing productivity.

[29] There exist several alternative decomposition methods that follows this tradition. See Foster *et al*. (1998) for further discussions on alternative decomposition methods.

Table 10 reports this decomposition. During the 1980's TFP dropped, mostly driven by a negative contribution of within-plant productivity growth. During most of the 1990's, however, TFP grew significantly with a positive, although less important contribution of the within-plant effect. Only by the end of the decade, during the economic slowdown, the within-plant term is negatively correlated with the overall change in TFP. In all periods, total reallocation is large and positive. Had the reallocation term been zero, the drop in TFP would have been 3 to 4 times larger in the 1980's. The positive total reallocation effect is mostly driven by the cross effect over all subperiods. The sign of this term reflects a positive covariance between shares and productivity changes; i.e., that production is being redistributed towards plants that become more productive. The between and cross effects offset each other in all periods, indicating that the plants with larger share growth were plants that initially were less productive than the average, but that exhibited positive withn-plant TFP growth.

Overall, both within plant efficiency changes and reallocation effects have been relevant for aggregate productivity dynamics in Chile during the last two decades. Although the contribution of each source of productivity gains has varied over time, reallocation has positively contributed in a larger magnitude during periods of negative or low growth; i.e. during 1981-83 and 1997-99.[30] Furthermore, the positive contribution of within-plant efficiency gains observed in the 1990s, is consistent with the existence of a lag between the implementation of major structural reforms and their complete effect on the economy. Most reforms were undertaken during the late 1970s and early 1980s. Once reforms were completed, unbounded within-plants efficiency gains driven by technology adoption and innovation occurred.

5. Concluding Remarks

Total factor productivity varies widely across plants in Chile. Even within the same sector and at any moment in time, plants display large differences in efficiency. We showed that these differences in efficiency are a quantitatively relevant source of the observed heterogeneity in the behavior of plants.

We then used these plant-level TFP estimates to provide a complete characterization of aggregate efficiency dynamics. We find that all sources of TFP growth -- within plant increases in productivity, the reallocation of resources across incumbent plants, and the process of entry and exit of plants -- are relevant

Market oriented policies promote technology adoption and innovation, and facilitate the process of reallocation of resources from less to more efficient economic units. Exposing firms to the best practice is key in generating conditions that promote aggregate growth.[31] Our results suggest that there might be large costs associated with policies that

[30] See Caballero and Hammour (1994) for a formalization of the connection between efficiency and reallocation during the recessions.

[31] Baily and Solow (2001) provide international evidence of the connection between the intensity of competition, the observed differences in TFP across firms, and aggregate efficiency.

alter the natural process of birth, expansion, and death of plants: growth may be retarded and development limited. As better plant-level data are collected and as a mapping between policies and productivity is constructed, we should be able to better understand the recent evolution of a wide range of economic experiences, both in the short and long run.

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Table 1. Production Function Estimates

	Balanced Panel		Full Sample				
	OLS	Fixed Effects	OLS	Fixed Effects	OP All obs.	OP Positive Investment	LP Positive Electricity
Food products (311)							
Skilled Labor	**0.395**	**0.109**	**0.428**	**0.174**	**0.366**	**0.346**	**0.288**
	0.017	0.016	0.008	0.008	0.008	0.011	0.008
Unskilled Labor	**0.249**	**0.334**	**0.451**	**0.380**	**0.415**	**0.309**	**0.370**
	0.018	0.021	0.009	0.011	0.009	0.012	0.009
Capital	**0.405**	**0.142**	**0.320**	**0.091**	**0.294**	**0.441**	**0.279**
	0.010	0.016	0.004	0.007	0.019	0.035	0.009
Sum of Coefficients	1.048	0.585	1.199	0.646	1.075	1.096	0.937
N Observations	3844	3844	16725	16725	14596	6411	14298
Beverages (313)							
Skilled Labor	**0.552**	**0.213**	**0.647**	**0.275**	**0.620**	**0.580**	**0.511**
	0.048	0.060	0.030	0.037	0.030	0.034	0.031
Unskilled Labor	**0.656**	**0.558**	**0.588**	**0.467**	**0.561**	**0.472**	**0.464**
	0.062	0.083	0.037	0.046	0.037	0.042	0.037
Capital	**0.184**	**0.117**	**0.133**	**0.126**	**0.092**	**0.211**	**0.184**
	0.027	0.034	0.014	0.021	0.022	0.045	0.036
Sum of Coefficients	1.392	0.888	1.367	0.868	1.272	0.014	1.159
N Observations	476	476	1593	1593	1397	734	1375
Textiles (321)							
Skilled Labor	**0.295**	**0.056**	**0.447**	**0.210**	**0.438**	**0.402**	**0.416**
	0.030	0.034	0.013	0.016	0.013	0.016	0.014
Unskilled Labor	**0.563**	**0.490**	**0.429**	**0.441**	**0.424**	**0.356**	**0.373**
	0.032	0.039	0.016	0.019	0.016	0.019	0.017
Capital	**0.101**	**0.138**	**0.155**	**0.087**	**0.157**	**0.164**	**0.166**
	0.019	0.028	0.008	0.011	0.035	0.075	0.034
Sum of Coefficients	0.959	0.684	1.031	0.738	1.018	0.922	0.955
N Observations	837	837	4978	4978	4231	1857	4161
Wood products (331)							
Skilled Labor	**0.357**	**0.174**	**0.446**	**0.243**	**0.407**	**0.425**	**0.355**
	0.042	0.055	0.016	0.020	0.016	0.020	0.016
Unskilled Labor	**0.677**	**0.636**	**0.604**	**0.675**	**0.544**	**0.433**	**0.477**
	0.054	0.064	0.018	0.025	0.018	0.023	0.019
Capital	**0.150**	**0.088**	**0.153**	**0.060**	**0.147**	**0.292**	**0.252**
	0.034	0.041	0.009	0.013	0.049	0.065	0.034
Sum of Coefficients	1.185	0.898	1.202	0.978	1.099	1.149	1.083
N Observations	509	509	4425	4425	3717	1618	3635

Table 1 Continued. Production Function Estimates

	Balanced Panel		Full Sample				
	OLS	Fixed Effects	OLS	Fixed Effects	OP All obs.	OP Positive Investment	LP Positive Electricity
Papers products (341)							
Skilled Labor	**0.012**	**0.097**	**0.505**	**0.174**	**0.483**	**0.469**	**0.460**
	0.094	0.098	0.028	0.031	0.028	0.032	0.028
Unskilled Labor	**0.161**	**0.452**	**0.401**	**0.219**	**0.411**	**0.336**	**0.372**
	0.067	0.114	0.031	0.030	0.033	0.037	0.032
Capital	**0.583**	**0.253**	**0.211**	**0.134**	**0.297**	**0.279**	**0.161**
	0.071	0.146	0.016	0.021	0.046	0.086	0.080
Sum of Coefficients	0.755	0.803	1.117	0.528	1.192	1.084	0.992
N Observations	80	80	1051	1051	881	499	869
Printing and Publishing (342)							
Skilled Labor	**0.395**	**0.379**	**0.404**	**0.254**	**0.339**	**0.341**	**0.299**
	0.058	0.067	0.015	0.019	0.016	0.018	0.016
Unskilled Labor	**0.480**	**0.275**	**0.473**	**0.249**	**0.396**	**0.359**	**0.341**
	0.063	0.053	0.019	0.020	0.020	0.023	0.020
Capital	**0.298**	**0.053**	**0.215**	**0.156**	**0.087**	**0.454**	**0.242**
	0.057	0.068	0.010	0.014	0.101	0.053	0.053
Sum of Coefficients	1.172	0.706	1.092	0.659	0.822	1.154	0.882
N Observations	220	240	2274	2294	1913	773	1887
Chemicals products (352)							
Skilled Labor	**0.423**	**0.162**	**0.553**	**0.186**	**0.470**	**0.431**	**0.513**
	0.036	0.040	0.020	0.022	0.020	0.022	0.020
Unskilled Labor	**0.210**	**0.325**	**0.231**	**0.276**	**0.197**	**0.142**	**0.212**
	0.035	0.038	0.019	0.022	0.020	0.022	0.021
Capital	**0.362**	**0.309**	**0.263**	**0.114**	**0.313**	**0.465**	**0.361**
	0.029	0.041	0.013	0.016	0.060	0.075	0.081
Sum of Coefficients	0.994	0.796	1.046	0.576	0.979	1.039	1.086
N Observations	700	700	2630	2630	2317	1502	2252
Metal products (381)							
Skilled Labor	**0.333**	**0.221**	**0.448**	**0.259**	**0.413**	**0.386**	**0.390**
	0.023	0.029	0.012	0.015	0.012	0.014	0.012
Unskilled Labor	**0.441**	**0.375**	**0.472**	**0.437**	**0.442**	**0.359**	**0.407**
	0.027	0.032	0.014	0.018	0.014	0.016	0.015
Capital	**0.303**	**0.185**	**0.189**	**0.114**	**0.224**	**0.275**	**0.205**
	0.014	0.025	0.007	0.011	0.035	0.060	0.044
Sum of Coefficients	1.076	0.780	1.110	0.811	1.080	1.021	1.002
N Observations	955	955	5689	5689	4674	2341	4612

Standard errors in parentheses. The standard errors of the capital coefficient were estimated through a boostrap using 500 replicators.

Table 2. Ratio of Percentiles
(Percentile 90 / Percentile 10)

Year	Food Products 311	Beverages 313	Textiles 321	Wood Products 331	Papers Products 341	Printing and Publishing 342	Chemicals products 352	Metal Products 381
1980	7.76	8.99	5.35	8.79	4.55	7.23	4.98	5.17
1981	8.47	15.60	6.27	8.93	4.80	7.59	6.14	4.61
1982	10.59	14.44	6.22	9.87	4.57	5.41	6.12	6.36
1983	10.13	10.44	6.39	12.07	6.22	4.80	5.34	6.27
1984	8.84	8.29	5.66	10.08	8.69	5.90	5.24	5.41
1985	9.93	8.78	5.30	9.19	8.70	4.45	4.58	6.04
1986	13.09	9.26	7.90	9.28	11.80	4.07	4.87	4.65
1987	11.74	8.07	5.24	8.77	11.21	5.83	3.99	4.87
1988	13.37	9.76	5.12	6.83	10.95	5.94	5.63	5.53
1989	10.22	7.04	5.84	6.71	13.58	5.23	4.73	4.61
1990	9.96	8.19	5.34	5.35	6.98	6.57	3.80	4.41
1991	9.50	6.44	6.30	5.02	8.95	6.40	6.05	4.69
1992	7.77	5.15	4.82	5.47	6.71	5.23	4.59	4.27
1993	7.47	8.34	5.42	5.20	8.08	4.15	5.50	4.04
1994	6.94	8.66	4.69	5.45	8.72	3.77	5.61	4.29
1995	7.14	5.78	4.54	6.29	11.75	5.90	5.12	3.97
1996	7.51	7.98	5.02	5.19	6.48	5.27	4.92	4.74
1997	7.30	7.63	5.11	7.47	7.88	4.49	6.35	4.12
1998	7.28	8.63	5.54	6.56	7.21	5.35	5.13	4.31
1999	7.48	13.98	4.42	7.44	5.85	5.04	4.72	5.33

Figures in thousands of 1985 Chilean Pesos

Table 3. Weighted Average Productivity According to the Ratio of Export to Sales.

Ratio Export to Sales %	Food Products 311	Beverages 313	Textiles 321	Wood Products 331	Papers Products 341	Printing and Publishing 342	Chemicals products 352	Metal Products 381
0	2141	2816	2666	1008	6446	2525	850	2331
Greater than 0	3040	2335	2997	1087	6393	4295	964	2933
[0, 5)	2556	2765	2693	993	6092	3295	932	2446
[5, 10)	4523	1619	2700	595	5108	2724	788	3200
[10, 20)	3506	1550	2855	570	4933	1901	995	2978
[20, 30)	1724	1909	2421	1252	3309	1804	861	2589
[30, 40)	2258	1727	2475	846	5440	2113	663	1481
[40, 50)	1769	2099	5045	755	6941	2371	223	1778
Over 50	1877	3114	3546	1329	7385	2431	539	1868

Figures in thousands of 1985 Chilean pesos.

Table 4. Weighted Average Productivity of Continuing, Entering and Exiting Plants

				Relative to Incumbents	
	Incumbents	Startups	Shutdowns	Startups	Shutdowns
Food Products (311)	2531	2022	3591	0.80	1.42
Beverages (313)	2697	1141	2514	0.42	0.93
Textiles (321)	2785	3409	3116	1.22	1.12
Wood Products (331)	1041	1010	1557	0.97	1.50
Papers Products (341)	6426	2649	5193	0.41	0.81
Printing and Publishing (342)	3195	3350	1803	1.05	0.56
Chemicals products (352)	911	880	1534	0.97	1.68
Metal Products (381)	2538	3360	3362	1.32	1.32

Productivity in thousands of 1985 Chilean pesos.

Table 5. Tests of First Order Stochastic Dominance
P-Values

Food Products (311)	0.0102
Beverages (313)	0.0776
Textiles (321)	0.0000
Wood Products (331)	0.0000
Paper Products (341)	0.0269
Printing and Publishing Products (342)	0.0265
Chemical Products (352)	0.3402
Metal Products (381)	0.0057

Table 6. Probability of Plant Death

	Coefficient		Marginal Effect	
	Productivity	Capital Stock	Productivity	Capital Stock
Food Products (311)	-7.17E-05	-1.88E-07	-1.87E-05	-4.91E-08
	1.49E-05	2.95E-08	3.88E-06	7.67E-09
Beverages (313)	-2.16E-04	-2.26E-07	-6.13E-05	-6.42E-08
	3.97E-05	7.50E-08	1.10E-05	2.12E-08
Textiles (321)	-2.33E-04	-2.97E-07	-6.05E-05	-7.71E-08
	2.30E-05	7.51E-08	5.85E-06	1.94E-08
Wood Products (331)	-7.64E-05	-3.98E-07	-2.52E-05	-1.31E-07
	4.94E-05	9.65E-08	1.63E-05	3.18E-08
Paper Products (341)	-1.58E-05	-5.72E-09	-3.41E-06	-1.23E-09
	1.94E-05	5.93E-09	4.17E-06	1.27E-09
Printing Products (342)	-1.01E-04	-4.87E-07	-2.67E-05	-1.28E-07
	4.70E-05	1.48E-07	1.24E-05	3.75E-08
Chemical Products (352)	2.64E-05	-1.22E-07	5.15E-06	-2.37E-08
	3.65E-05	8.16E-08	7.13E-06	1.59E-08
Metal Products (381)	-4.65E-05	-5.41E-07	-1.14E-05	-1.33E-07
	2.15E-05	1.21E-07	5.28E-06	2.94E-08
All sectors	-1.98E-05	-2.69E-08	-5.30E-06	-7.20E-09
	3.20E-06	6.70E-09	8.56E-07	1.80E-09

The second entry is the standard error.

Table 7. Productivity and Plant-level Employment

	Productivity	Capital Stock
Food Products (311)	0.141	0.276
	0.007	0.003
Beverages (313)	0.213	0.311
	0.021	0.009
Textiles (321)	0.111	0.357
	0.018	0.009
Wood Products (331)	0.149	0.331
	0.014	0.007
Paper Products (341)	0.111	0.373
	0.035	0.009
Printing Products (342)	0.350	0.347
	0.027	0.010
Chemical Products (352)	0.085	0.395
	0.026	0.009
Metal Products (381)	0.136	0.284
	0.014	0.005
All sectors	0.135	0.308
	0.005	0.002

OLS regressions including a full set of time dummies, and t and t-1 average employment. The pooled regression also includes a full set of sectoral dummies. Productivity is current plant TFP. Capital stock is positive. The second entry is the standard error. Employment is t-1 and t average adjusted employment.

Table 8. Productivity and Plant-level Capital Stock

	Productivity	Employment
Food Products (311)	0.184	1.588
	0.017	0.014
Beverages (313)	-0.140	1.354
	0.047	0.043
Textiles (321)	-0.004	1.166
	0.032	0.020
Wood Products (331)	-0.220	1.356
	0.030	0.022
Paper Products (341)	0.142	1.758
	0.070	0.035
Printing Products (342)	-0.113	1.439
	0.058	0.028
Chemical Products (352)	-0.270	1.418
	0.044	0.026
Metal Products (381)	-0.091	1.565
	0.034	0.023
All sectors	0.055	1.485
	0.011	0.008

OLS regressions including a full set of time dummies, and t and t-1 average employment. The pooled regression also includes a full set of sectoral dummies. Productivity is current plant TFP. Capital stock is positive. The second entry is the standard error.

Table 9. Lumpy Gross Investment

	Marginal Effect		
	II	III	IV
Food Products (311)	0.087	0.113	0.180
	0.011	0.011	0.010
Beverages (313)	0.110	0.108	0.139
	0.027	0.027	0.027
Textiles (321)	0.105	0.146	0.132
	0.019	0.019	0.019
Wood Products (331)	0.092	0.157	0.156
	0.021	0.020	0.020
Paper Products (341)	0.126	0.214	0.056
	0.034	0.031	0.039
Printing Products (342)	0.117	0.185	0.175
	0.028	0.027	0.028
Chemical Products (352)	0.078	0.071	0.066
	0.016	0.016	0.016
Metal Products (381)	0.094	0.119	0.132
	0.017	0.017	0.017
All sectors	0.097	0.131	0.154
	0.007	0.007	0.007

Probit regressions including a full set of time dummies, and t and t-1 average employment. The pooled regression also includes a full set of sectoral dummies. Productivity is current plant TFP. The second entry is the standard error.

Table 10. Decomposition of TFP Growth
(all sectors)

	Total	Within	Between	Cross	Entry	Exit	Net entry	Total Reallocation
1983-81	-246.4	-697.0	-254.2	658.4	17.4	-29.0	46.4	450.6
1983-90	-34.8	-144.9	-271.9	367.1	-67.8	-82.7	14.9	110.1
1990-97	713.3	137.2	-268.2	570.0	82.1	-192.2	274.3	576.1
1997-99	634.9	-71.0	-269.0	757.6	333.2	115.9	217.2	705.9
1981-99	757.8	286.4	-144.3	263.5	502.6	150.5	352.1	471.3

Figures in thousands of 1985 Chilean pesos.

Figure 1. Weighted Average Productivity at the Industry Level, (1980=100)

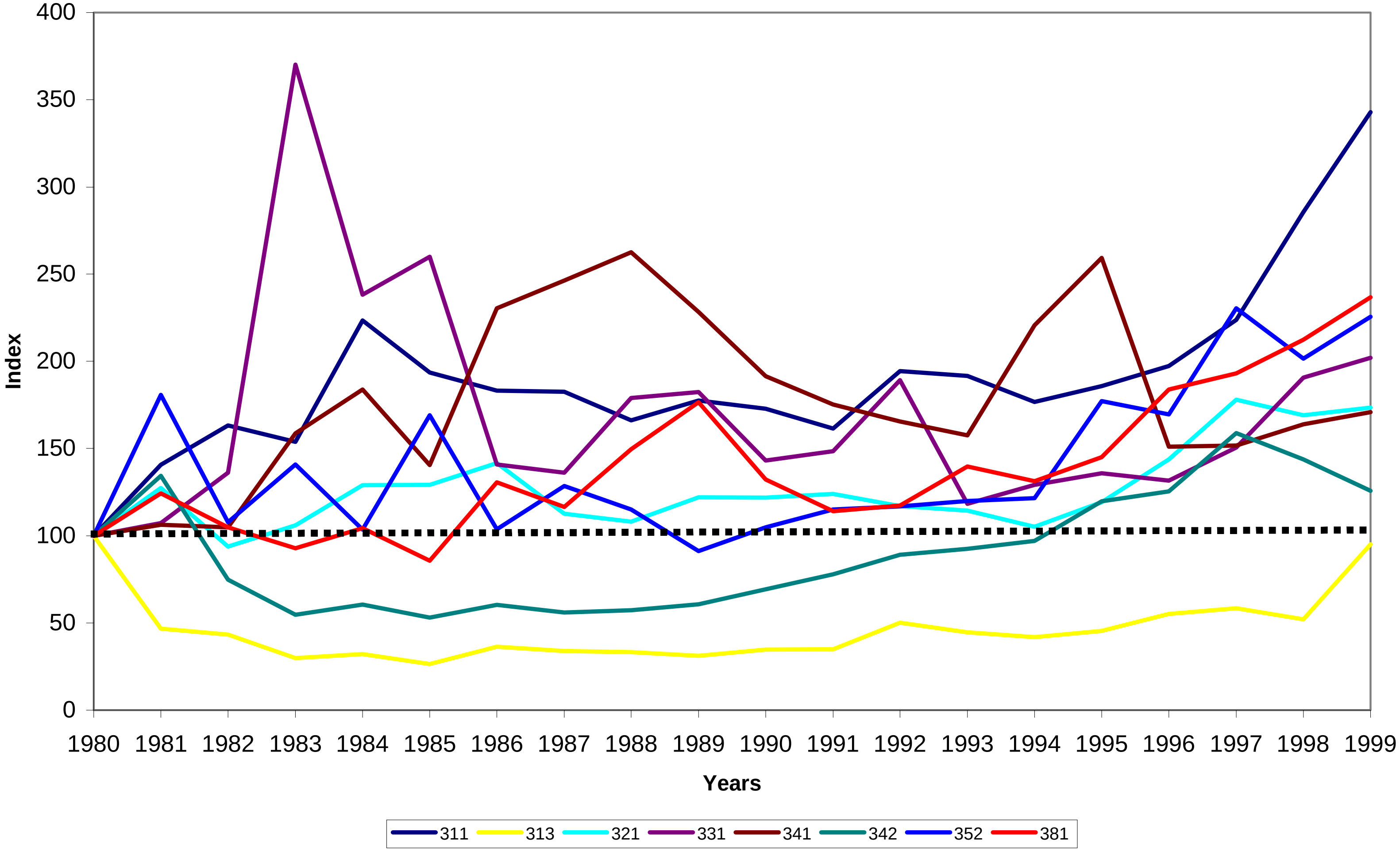

Figure 2a. TFP by Cohort

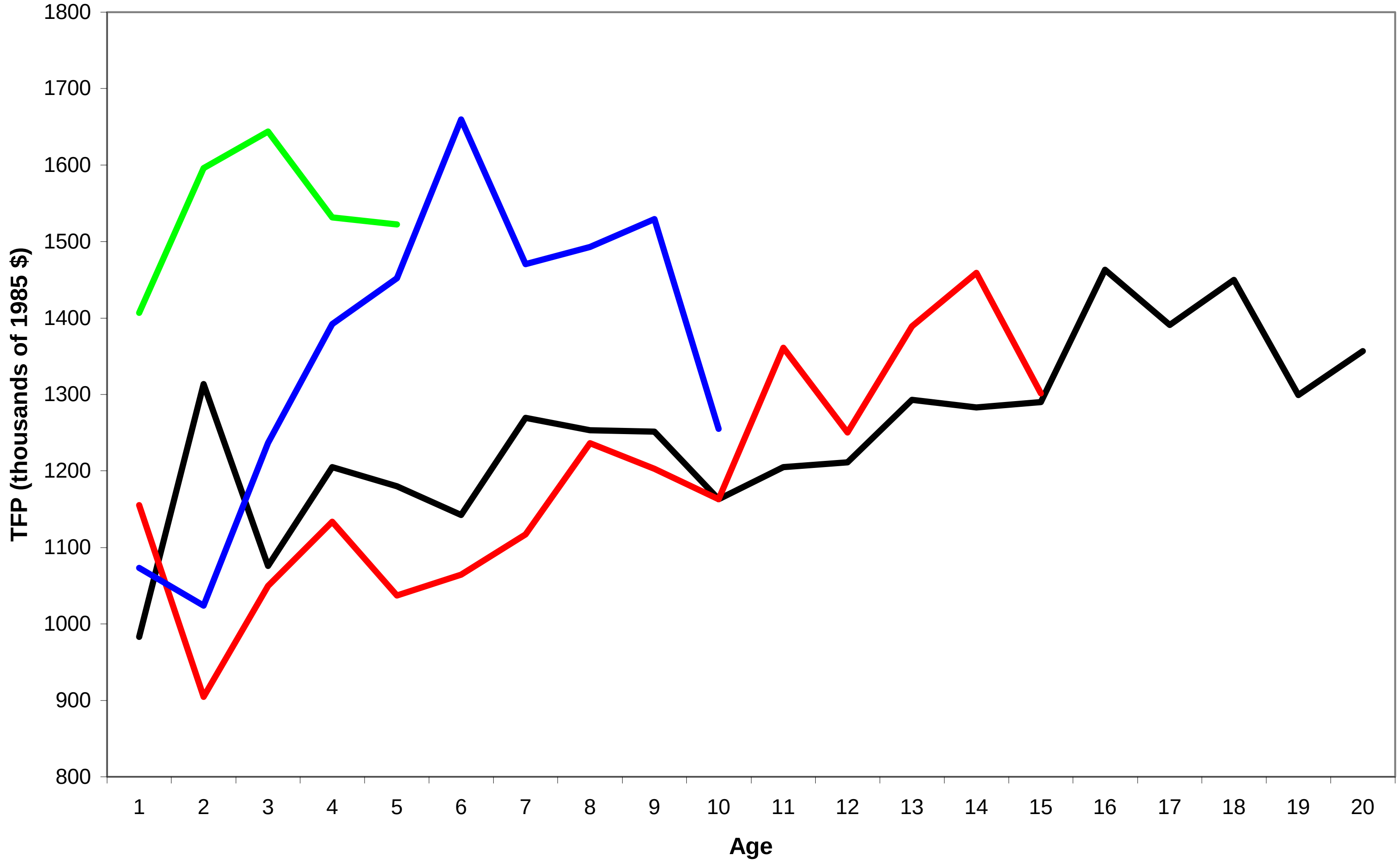

Figure 2b. TFP Decomposition: Age Effects

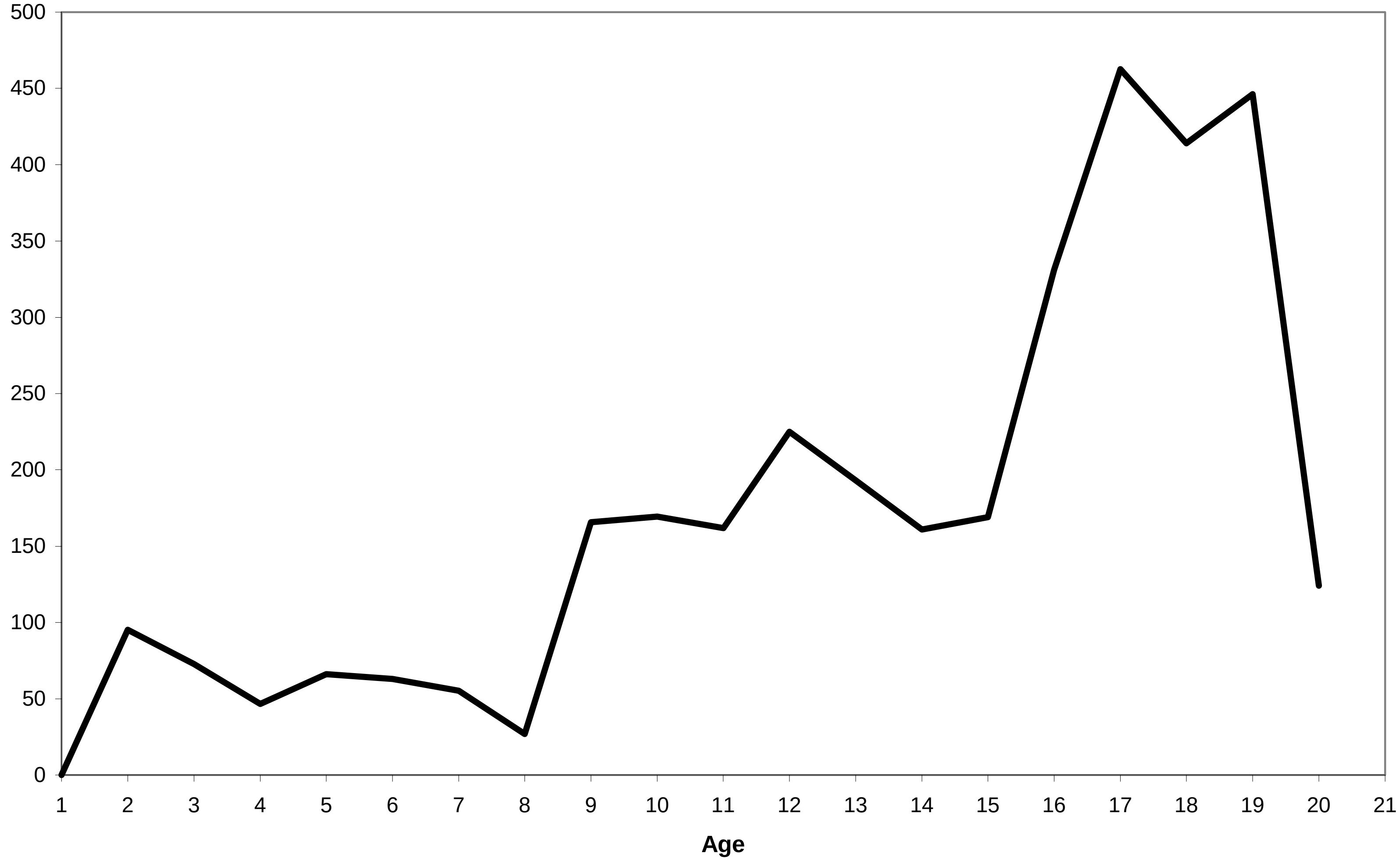

Figure 2c. TFP Decomposition: Cohort Effects

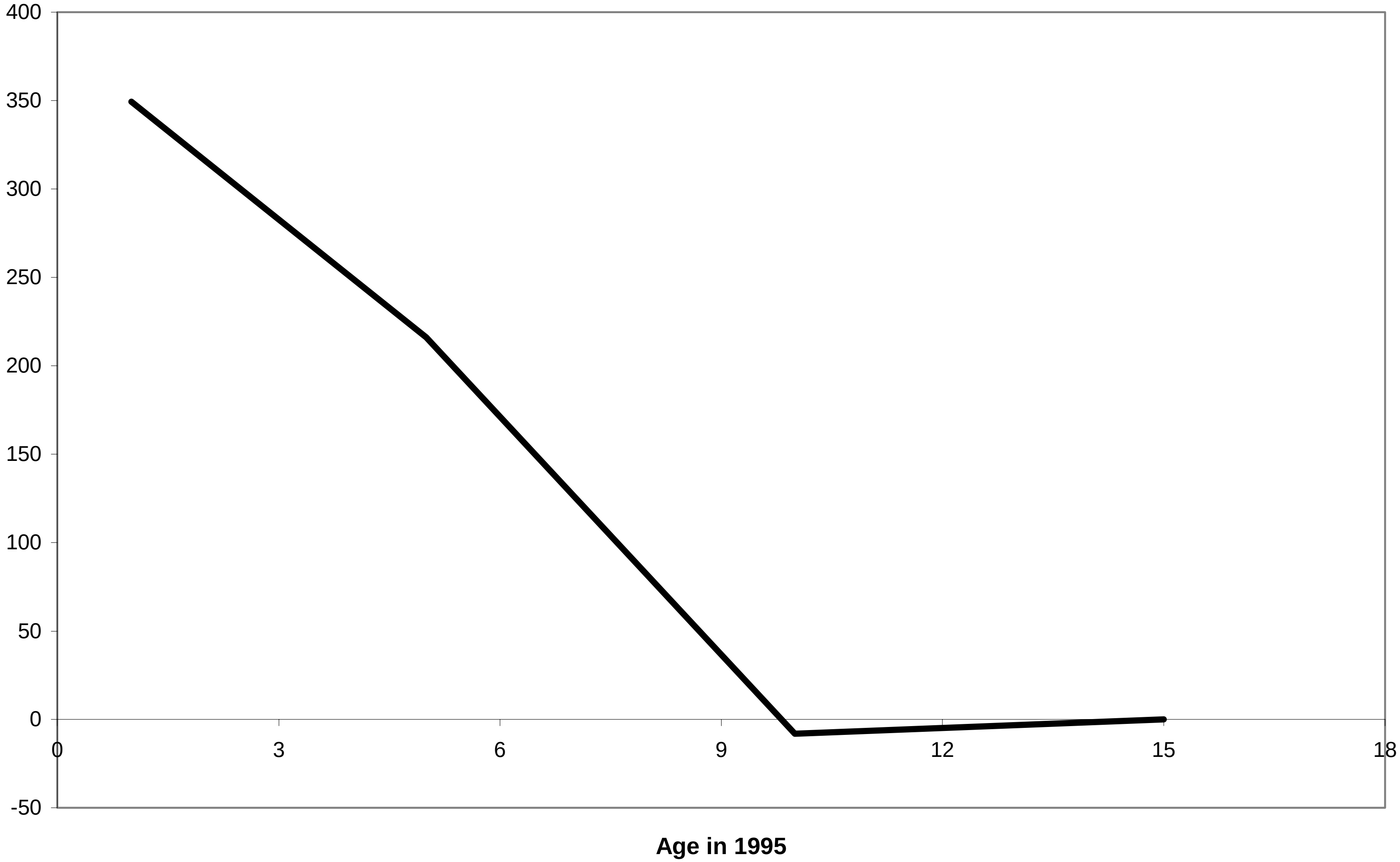

Figure 2d. TFP Decomposition: Year Effects

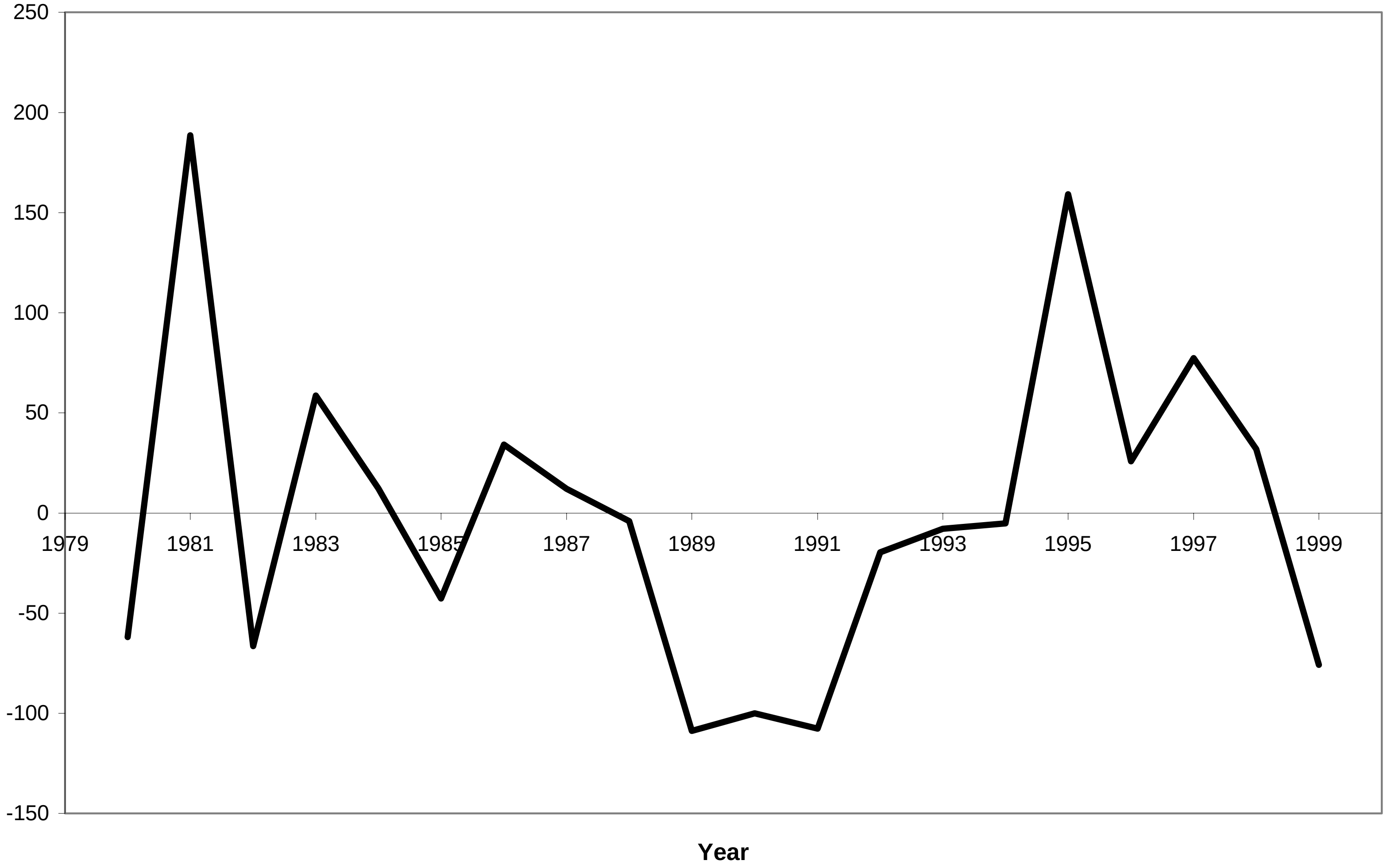

Figure 3. Cumulative Distribution of Productivity (all sectors)