The Importance of Absorptive Capacity for Gains from Foreign Technology Spillovers: A Stochastic Frontier Analysis[1]

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1. Introduction and Overview

In the literature on economic growth in developing countries, international technology flows have gained growing attention.[2] International technology can 'flow' from the originating country to the receiving country in several ways. Among them, foreign direct investment and trade in intermediate inputs and capital goods have been the subject of a great deal of empirical work. Most studies choose firms or establishments as units of analysis and adopt a neoclassical production function framework in which the average response of the endogenous productivity variable to a change in one of the exogenous variables (such as the intensity of FDI and import of intermediate inputs and capital goods) is estimated by means of classical regression analysis. Deviations from this behaviour are thus seen as realisations of a random noise process. If, for example, productivity performances show an increasing variance over time, the production function approach does not yield any insights, as the effect is just an increase in the variance of the stochastic random noise process. While this approach is useful in drawing general conclusions about the factors affecting the productivity performance of an industry or a group of industries, the causes of observed heterogeneity within them remain unknown.

In this paper, we adopt an alternative approach—the *stochastic frontier analysis* (SFA) approach[3]—to examine the effect of foreign technology spillovers on domestic productivity growth. In SFA, typical techniques do not estimate 'average relationships' between variables, but relationships for best-practice establishments. This implies that we estimate relationships between inputs (capital, labour), technological change (technology spillovers) and output (value added) for best-practice establishments for several years to get indications of the degree to which international technology spillovers affected productivity growth. Simultaneously, we link the underperformance of other establishments to variables that relate to the evolutionary concept of absorptive capacity (Cohen and Levinthal 1990), such as labour quality, presence and strength of links to foreign markets, ownership, experience, etc. These results are quantifications of the failure to fully assimilate international technology spillovers, and thereby to raise productivity to its potential level. We are thus able to account for the heterogeneities across establishments in terms of the differences in their absorptive capacity.

We then connect the SFA estimation results to a decomposition framework. It is well-known that Indonesia's manufacturing sector has a dual nature.[4] While many establishments still use outdated machinery, others have the world's most advanced equipment installed. Of course, the productivity levels that could be attained in these modern establishments are much higher than those in the old ones. Los and Timmer (2005) proposed an 'appropriate technology' accounting framework to quantify the contributions of three sources of labour productivity growth in a model that takes such differences in capital stocks explicitly into

[1] This is a substantially modified version of Jacob and Los (forthcoming).

[2] For an extensive overview of empirical studies see Keller (2004).

[3] The foundations for this technique were laid in Aigner and Chu (1968). A modern textbook is Kumbhakar and Lovell (2000).

[4] See, for instance, Hill (1996) and the recent PhD thesis by van Dijk (2005), which offers in-depth economic and technological analyses of the Indonesian pulp and paper industry.

account. The three components of labour productivity growth are: (1) *innovation* that represents the changes in the position of the frontier or best-practice performances for several technologies; (2) *assimilation* that refers to effectively learning from the superior performance of other units employing similar equipment; and (3) *creating spillover potential* that relates to the effects of investments in potentially more productive technologies. Los and Timmer (2005) applied this methodology to macroeconomic data. We adopt several parts of their methodology to investigate how innovations, changes in absorptive capacity and technologies operated contribute to the productivity-growth experiences of Indonesia's manufacturing establishments.

Our analysis covers establishments in 65 5-digit industries for the period 1988-1995 (for more details, see section 4). The high level of disaggregation means that the units of analysis—establishments—produce 'similar' products. Finally, we compare the results across five broad groups of industries.

The following section briefly outlines the theories of productivity growth that are relevant for our empirical approach. The third section proposes our methodology; it deals with the accounting framework, grounded on the 'appropriate technology' and 'assimilationist' theories, and discusses the way in which frontiers and distances to these frontiers are estimated. The fourth section is devoted to data issues. The results are presented in the fifth section. The final section concludes, and proposes a few directions for future research.

2. Selected Theories on Productivity Growth

Convergence (or its absence) of labour productivity levels has attracted a lot of attention, both from economic theorists and from more empirically oriented scholars. Although it is hard to classify theories in a field characterized by synthesis and hybridization, roughly two categories of theories can be discerned. We follow Nelson and Pack (1999) in using the labels "accumulation theories" and "assimilation theories". Accumulation theories basically assume that raising capital intensities (be it physical capital or human capital) automatically leads to labour productivity growth, although increasingly more investment is required for a given productivity gain. In this view, labour productivity changes are governed by production functions that are common to the countries, sectors or firms under consideration. This perspective implies that technology is completely a public good, in the sense that an innovation by one firm or country can and will immediately be copied by others.

Assimilation theories challenge this view. Here, technology is seen as something that does not automatically and immediately flow across firms or countries. Instead, only firms or countries that have invested sufficiently in their "absorptive capacities" will be able to turn innovations developed elsewhere into productivity gains for themselves. Nelson and Pack (1999), for example, note that newly industrialised countries such as Taiwan did not have any experience at all in using technologies related to electronics in the 1960s. In the 1980s, this had radically changed, while other countries had not developed any activity at all in this field. According to Nelson and Pack (and us), it is very unlikely that differences in investment in capital goods alone can be held responsible for such differences. In the view of assimilationists, policies to stimulate entrepreneurship and eagerness to learn have been much more important. Such a view on macroeconomic performance can, with relatively minor modifications, be transferred to studies at firm or plant level. The resource-based view of the firm (see Teece, 2000, for example) stresses that long-run firm performance is mainly determined by learning capabilities.

In this paper, we will differentiate between two barriers to attaining a labour productivity level attained by another plant. The first type of barrier relates most strongly to issues mentioned above. Pack (1987) and Van Dijk (2005, Ch. 8) show that plants that are similar in terms of the types of machines installed attain widely varying productivity levels.[5] Apparently, learning and organizational capabilities are not identically distributed across plants, which shows up in different productivity figures for plants with more or less identical equipment installed.

The second type of barrier is quite closely associated with what Abramovitz (Abramovitz 1989) labelled "technological incongruence". He notes, drawing on the post-second world war catching-up experience of OECD economies to the US productivity levels, that an important pre-condition for catch up is the similarity in the endowment of land, other natural resources, tangible capital and human skills between the follower and leader countries. A similar idea has recently been proposed in the form of a formal model by Basu and Weil (1998). The model treats technologies as specific to particular combinations of inputs, or in other words, capital-labour ratios. Firms or countries benefit from new technologies only if these are comparable to the existing technologies which they operate on.[6] In the longer run, non-appropriate innovations can become appropriate if the firm or country invests to such an extent that it shifts its technology to a capital intensity level comparable to the innovating firm or country.[7] An important feature of the model is that new technologies 'mature' to reach their potential levels through *learning by doing*; and, these potential levels are higher at higher levels of capital per worker.[8] The latter argument could well have relevance in a dual economy like Indonesia.

3. Methodology

This section describes the empirical methodology we adopt. It consists of two parts. First we outline the decomposition of labour productivity growth (or decline) of an establishment into the effects of innovation, assimilation and equipment upgrading, which creates potential for spillovers. We then discuss the estimation methods required to arrive at the quantification of these effects.

3.1. Identifying the Sources of Growth

Los and Timmer (2005) decomposed labour productivity growths rates of a group of countries, between 1970 and 1990, into the effects of movements towards the frontier, or changes in technical efficiency (assimilation), movements of the frontier (innovation), and capital deepening (creating potential). The decomposition form itself was popularised by Kumar and Russell (2002), but Los and Timmer were the first to link their results to the

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[5] Pack (1987) studied the performance of textile plants in Kenya, the Philippines and the UK. Van Dijk (2005) focused on the productivity levels of paper-making plants in Indonesia and Finland.

[6] Basu and Weil (1998) illustrate this concept by arguing that new knowledge pertaining to the very capital-intensive maglev-trains in Japan will not be useful to transporters in Bangladesh using very capital-extensive bullock carts technologies.

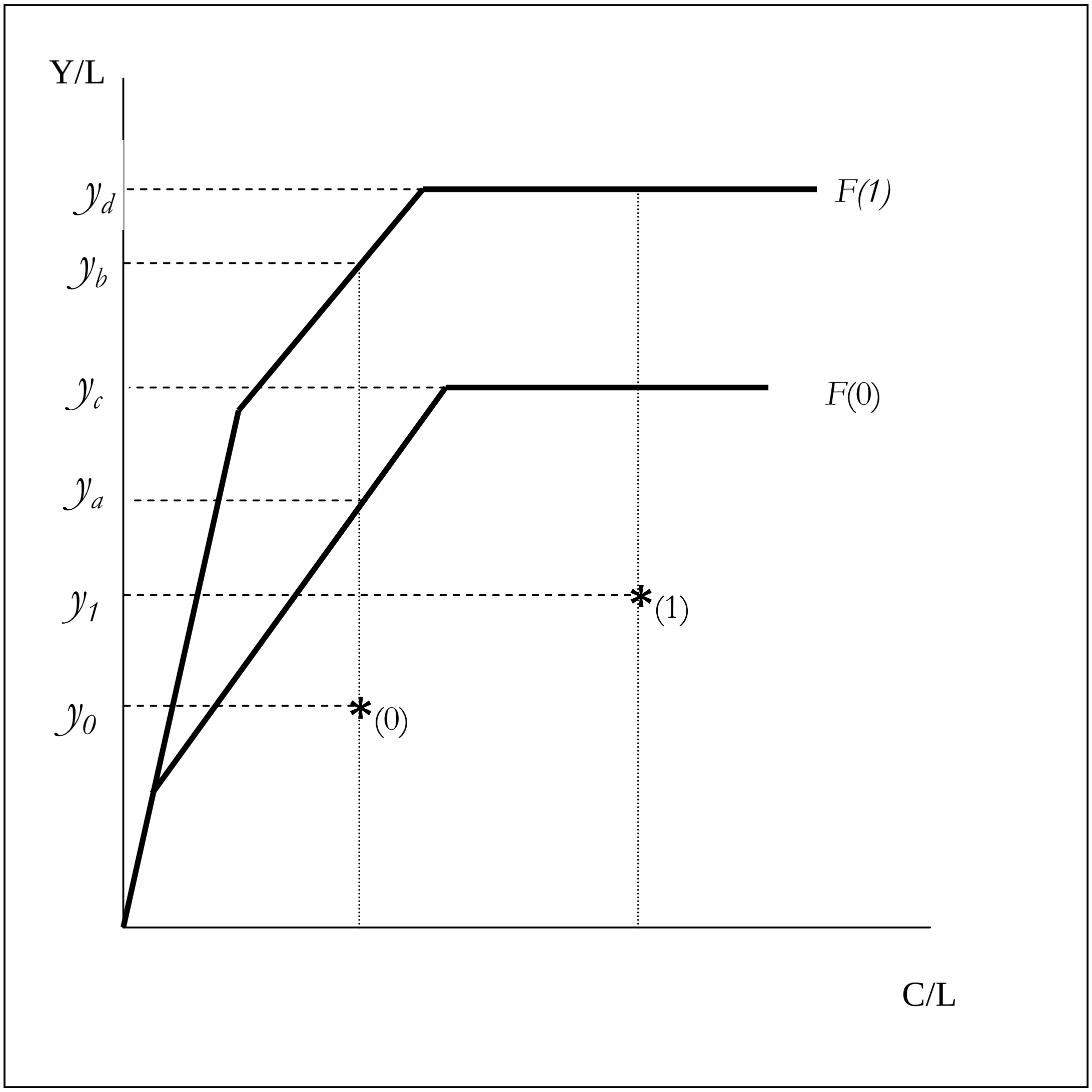
[7] Atkinson and Stiglitz (1969) introduced the concept of 'localised learning by doing' by which they suggested that firms improve the productivity of a particular mix of capital and labour over time. Basu and Weil (1998) extended this notion by emphasizing the importance of 'localised knowledge spillovers'. Localised spillovers, however, does not mean that firms gain spillovers with regard to only a specific input mix, but also similar techniques.

[8] The Basu and Weil model predicts that an increase in the saving rate will result in a faster growth for the follower country than for the leader. This is because the follower is able to move 'quickly to the front of the pack, taking advantage of the relatively mature technology at the rear' (Basu and Weil 1998, p.1051).

theories discussed in the previous section. Our approach starts from a similar perspective. It is novel in the sense that it explicitly relates the observable characteristics of the establishments to the decomposition results.

Figure 1 shows an establishment's actual labour productivity levels y_0 and y_1 in an industry with production frontiers f^0 and f^1 for periods 0 and 1, respectively.

FIGURE 1 *Labour Productivity Growth Decomposition*



The labour productivity change (y1/y0) of this establishment can be decomposed in the following way:

$$\frac{y_1}{y_0} = \left(\frac{y_1}{y_d} \cdot \frac{y_a}{y_0}\right) \cdot \left(\frac{y_c}{y_a} \cdot \frac{y_d}{y_b}\right)^{0.5} \cdot \left(\frac{y_b}{y_a} \cdot \frac{y_d}{y_c}\right)^{0.5} \tag{1}$$

or

$$\left(1+\hat{y}^T\right) = \left(1+\hat{y}^A\right) \cdot \left(1+\hat{y}^C\right) \cdot \left(1+\hat{y}^I\right) \tag{2}$$

where $\hat{y}$ refers to the growth rate.

In the first term on the right hand side $(1+\hat{y}^A)$, a value of $\hat{y}^A$ larger than 0 indicates that the establishment under consideration has increased its labour productivity for the technology operated. In other words, it indicates that the establishment has been able to bring about an increased exploitation of technological potential (the maximum productivity observed for the equipment operated). We call this the *assimilation* effect.[9] The second explanatory factor $(1+\hat{y}^C)$ indicates the changes in labour productivity due to increases in capital intensity alone. While a higher capital intensity in itself does not generate higher labour productivity, it can lead to an upward shift in the attainable or the 'target' productivity levels, depending on the slope of the frontier. Therefore, a value greater than 0 for $\hat{y}^C$ can be interpreted as *creating potential*.[10] The third factor $(1+\hat{y}^I)$ points to the effect of localised technological change that results in the upward shift of the production frontier. Assuming that the establishment's capital intensity remains constant, a positive value for $\hat{y}^I$ indicates that it has benefited from an increase in the maximum attainable labour productivity levels for the given technologies (given a certain distance from the frontier). We call this the innovation effect.

Los and Timmer (2005) estimated the productivity frontiers for the beginning and end periods using data envelopment analysis (DEA). We follow a similar approach, but with the key difference that we derive the frontier labour productivity levels by means of SFA. This change of method has advantages and drawbacks. The major drawback is that truly localised innovation cannot be modelled, as the estimated elasticity of foreign R&D spillovers (the source of technological change) is the same across the full range of technologies (see the following two subsections, and in particular equation (7)). As a result, the shifts in the frontier labour productivity levels always amount to an identical proportional growth rate across the full range of technologies. The distance to the frontier, however, can well change, thereby allowing potentials for spillovers to change. The major advantage is that the location of the frontier is not very sensitive to measurement errors for a small number of firms. As is well known (see, e.g. Coelli *et al.* 1998), DEA results can be distorted quite a bit. In view of the sizeable measurement and reporting errors that are often found in establishment level surveys, especially in less developed countries, we feel that the net advantage of SFA as compared to DEA is clearly positive.

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[9] Below we will argue that our estimation framework allows us to decompose assimilation effects into 'explained assimilation' (explained by means of absorptive capacity indicators) and 'unexplained assimilation'.

[10] The usage of the terminology 'creating potential', instead of 'capital deepening', is in the spirit of the assimilationist view, as opposed to the accumulationist (neo-classical) view of growth. In this view, the increased 'potential' from an increase in capital-labour ratio cannot be automatically 'realised' unless the efficiency level at the final capital intensity is at least equal to, if not greater than, that at the initial capital intensity. This requires an increase in absorptive capacity in tune with the increase in the 'target' productivity level. As has been the case in a vast majority of less developed countries, their inability to enhance absorptive capacity and entrepreneurship stood in the way of their achieving growth similar to that in the East Asian NICs—despite comparable investment rates. Note in this context that the simple evocation of the term 'capital deepening', as is vogue in the contemporary literature on the empirics of growth, can therefore by highly misleading—masking many of the significant dynamics of growth.

3.2. Estimation Method

This subsection briefly discusses the SFA techniques in general, and the approach adopted in this paper in particular for estimating labour productivity frontiers and inefficiencies. These estimates are then employed to decompose industry-level labour productivity growth on the lines of the framework described above using figure 1.

In recent years, a number of studies have employed SFA for estimating and explaining inefficiencies of firms and establishments in industries. Until recently, the standard approach was a two-stage estimation procedure, in which the production frontier is first estimated. In the second stage, the resulting inefficiencies (the vertical distances from the observed productivities to the estimated frontier) are regressed on firm-specific variables (see e.g. Pitt and Lee 1981).[11] Estimation in the second stage, however, contradicts the assumption of identically distributed inefficiency effects that underlies the estimation of the stochastic frontier in the first stage. To overcome this methodological problem, several authors have suggested single-stage procedures for simultaneously estimating both the stochastic frontier and inefficiency functions.[12] The Battese and Coelli (1995) model is one such approach.

Consider the following production function for panel data.

$$y_{it} = \alpha + X_{it}\beta + \varepsilon_{it} \tag{3}$$

where y_{it} is the dependent variable corresponding to the i^{th} establishment and time t, X is a vector of explanatory variables, and ε_{it} is the composite error term. The latter consists of a white noise error v_{it}: $v_{it} \sim \text{iid } N\left(0, \sigma_v^2\right)$ and u_{it}. The two sets of disturbances are assumed to be independent. The u_{it}s are non-negative random variables associated with technical inefficiencies, and are assumed to be independently (but not identically) distributed as truncations (at zero) of the $N(\mu_{it}, \sigma_u^2)$ distribution, with

$$\mu_{it} = Z_{it}\delta \tag{4}$$

in which Z is a vector of observable, non-stochastic explanatory variables associated with technical inefficiency, and δ is a vector of unknown coefficients.[13]

In this model, the maximum likelihood method is used for the simultaneous estimation of the parameters of the frontier and technical inefficiency models—the unknown parameters βs,

[11] For a recent survey, see Wang (2003).

[12] Hill and Kalirajan (1993) adopt a different approach in their study of Indonesian firms in the garment industry. Based on the inefficiency scores estimated in the first stage, they employ a 'discriminant function analysis' in which differences between two groups of firms—Highly Technically Efficient firms and Highly Technically Inefficient firms—are related to their firm-specific characteristics. It may be noted that the discriminant function analysis does not require the aforementioned distributional assumptions on the dependent variable that the regression analysis requires.

[13] This is of course a restricted specification. As Wang (2003) notes, because uit has a truncated normal distribution, its variance is a function of not only μ_{it} but also σ^2_{it}, and therefore, heteroscedasticity of u_{it} can be modelled through a nonconstant μ_{it}, (Battese and Coelli 1995), a nonconstant σ^2_{it}, (Caudill et al. 1995) or both (Wang 2003). The last of these approaches (that is the unrestricted model) demands higher degrees of freedom than our samples can offer. Hence, we have decided against using this approach.

δs, σ_u^2 and σ_v^2. We computed the estimates using the FRONTIER software package (Coelli 1996). Battese and Coelli (1993) provide an expression for the conditional expectation of exp$(-u_{it})$ given ε_{it}. The maximum likelihood estimation of this function is used to estimate the technical efficiency index of the i^{th} firm at time t, based on the expected values conditional on the observed values of the explanatory variables in X and Z. When the productivity frontier is expressed in logarithms, the technical efficiency index (TEI) can be expressed as follows.

$$TEI_{it} = \exp(-u_{it}) \tag{5}$$

This index has a value between 0 and 1, with 0 ($u_{it}\rightarrow\infty$) indicating the least efficient, and 1 ($u_{it}=0$) the most efficient establishments.

Changes in TEI as defined in equation (5) denotes a part of the actual shift in labour productivity. When a change in TEI causes an upward shift, as in figure 1, it can be interpreted as associated with the assimilation of technology-specific knowledge. It is that part of the assimilation effect which can be explained by the changes in the indicators of absorptive capacity, given their estimated coefficients from the SFA model. The remainder of the upward shift cannot be explained, and is calculated as the difference between the actual growth in labour productivity and the predicted growth derived from the SFA model.

3.3. The Empirical Model

In our model, the production frontier of an industry takes a Cobb-Douglas form. The movements of the production frontier is dependent on the changes in the stock of knowledge available in the industry. In most less developed countries, and especially so in Indonesia, own technological efforts are virtually absent, and foreign technology is the key source of knowledge and hence technological progress. We therefore construct a measure of international R&D stock (*IRD*) to capture spillovers of knowledge to a given industry. The production frontier augmented to accommodate these knowledge flows is defined as follows.

$$Y_{it} = AK_{it}^{\beta_1} L_{it}^{\beta_2} IRD_t^{\beta_3} \tag{6}$$

where, Y_{it} is the value added of establishment i at time t, K the replacement value of capital, L the total number of workers, and *IRD* the international R&D stock representing the technology flows available to all establishments in the industry (see the following section for a fuller description of the variables). Dividing Y and K by L and taking logarithms, equation (6) becomes

$$y_{it} - l_{it} = \alpha + \beta_1(k_{it} - l_{it}) + \beta_3 ird_t + \varepsilon_{it} \tag{7}$$

where the lowercase symbols denote the variables in logarithms. In the transformation of equation (6) to (7), we impose the assumption of constant returns to scale in the rival inputs labour and capital.[14] We use equation (7) as the frontier function that will be estimated simultaneously with the inefficiency function, based on the procedure described in the previous subsection.

[14] The scale of operation of firms could be important in learning. This is because big firms have more contacts with suppliers, are represented stronger in professional associations, etc. To accommodate the learning effect of scale, we include the variable 'establishment size' in our inefficiency function. See equation (8)

Given that technology-embodied inputs have often shown to be an important channel of foreign technology diffusion, an establishment's access to imports might be a good proxy of its 'access to foreign technology'. Access to a source of technology does not, however, imply that the acquisition of technology is guaranteed. This is because technology is not entirely 'codified', and indeed often takes a highly 'tacit' form (Polanyi 1958). This is arguably more so when technology is embodied in imported capital or intermediate inputs, than in say, 'blue prints'. Therefore, the extent to which an establishment is able to 'absorb' the tacit knowledge related to new technologies can depend on the quality of its labour force. Evenson and Westphal (1995) proxy this by the proportion of scientists and engineers in an establishment's work-force.

The 'ownership structure' of an establishment can also be a significant factor influencing the capacity to assimilate knowledge. An establishment with foreign management control might be expected to run more productively than, for example, a non-professional, family-controlled enterprise. The 'foreign-connection' may enable the former to adapt itself much more quickly than the latter to global changes in technology, production relations, etc.

The performance of an enterprise as compared to other enterprises with similar technologies may also depend on its 'size'. As noted by Tybout (2000), in many less developed countries, the demand for manufactured products is skewed towards simple items which can be efficiently (and with a higher TFP) produced using cottage techniques. An opposite effect would be the operation of Schumpeterian dynamics that leads to greater learning efforts by large firms. This may result from scale economies, availability of internal resources in the presence of imperfect markets and/or uncertainties, synergies between technological, production, marketing and distribution activities, etc. The empirical evidence, mostly pertaining to advanced economies, shows no consensus, however (see Marsili 2001, for an overview).

Another factor that may influence technical efficiency is the 'age' of an establishment. Experienced establishments may enjoy the benefits of learning-by-doing. As Klepper (2002) argues, with increases in competitive conditions firms with greater experience have greater leeway in enhancing their capabilities.

Keeping these considerations in mind, we can write the inefficiency model as follows.

$$u_{it} = \delta_0 + \delta_1 Access_{it} + \delta_2 LQual_{it} + \delta_3 Foreign_{it} + \delta_4 Age_{it} + \delta_5 Size_{it} \tag{8}$$

where, *Access* represents access to technology spillover, defined as the share of imported material inputs in total material inputs; *LQual* stands for the quality of labour in an establishment, defined as the share of non-production (white-collar) workers in total employment; *Foreign* represents the proportion of foreign ownership in an establishment; *Age* is measured as the difference between the year of operation and the year of inception; and *Size* is defined as the logarithm of the total number of workers.

A final aspect to consider is the influence of factors observable only to the managers of an establishment, which are not reflected in a survey-based data set like ours. Such establishment-specific effects (or heterogeneities) may be related to other regressors of the model which may cause biased results. We therefore adopt the establishment-fixed-effect specification in our inefficiency model. The adoption of the fixed-effect specification in the frontier model requires that, as Green (2003) points out, most of the variation in the dependent variable is 'within' establishments. However, much of the variation in our dependent variable (logarithm of labour productivity) is 'between' establishments, with very little within-establishment variations. We have therefore decided against adopting the establishment-fixed-effect specification in the frontier model.

4. Data Issues

Our main data sources are two large establishment-level data sets, *backcast* and *statistic industri (SI),* constructed by the central statistics agency (*badan pusat statistik,* BPS) (See appendix section A, for a detailed description of the data sources, variables, cleaning processes, etc.). The data sets cover all large and medium-sized establishments in the manufacturing sector of the country, from 1975 to 2001. However, we will limit our analysis to the period 1988-95.[15] After applying cleaning procedures to account for duplications, reporting errors and data entry errors, we focus our analysis on industries defined at a low level of aggregation (5-digit classification). This allows us to investigate productivity growth for sets of establishments with homogeneous activities. Since the panel data SFA-approach is data-intensive, we select 65 industries for which at least 10 establishments are included in the data set. Furthermore, given that we capture technological change by means of international spillovers of technology, access to imported intermediate inputs (in the inefficiency function) is a key variable that reflects the international linkages of establishments. Therefore we choose only those establishments which have recorded a positive import of intermediate inputs every year. The industries under investigation are quite diverse, which allows us to identify inter-industry differences in the importance of absorptive capacity for productivity performance (see table A.2).

Finally, we should describe how we estimate the international R&D stock that captures technology flows. Since Indonesian firms do generally not undertake any formal R&D activities themselves, it can safely be assumed that new technology must come from abroad (Hill, 1996). Our admittedly poor, but widely accepted assumption if suitable output indicators of innovation are not available, is that technology production is proportional to R&D expenditures. We have data on R&D expenditures by industry for ten countries that together account for approximately 60% of the imports to Indonesia and about 85% of the total OECD R&D expenditure. The selection of this sample is justified because empirical evidence suggests that "it is not the intensity of import *per se* that matters, but rather the distribution of the countries of origin. The more you import from highly R&D intensive countries, the larger the impact of foreign R&D" (Lichtenberg and van Pottelsberghe (1998, p.1483). Apart from imports, technology purchase, technology collaboration and exports by Indonesian firms as well as foreign investment in the domestic market can all act as carriers of technology spillovers. To accommodate these different channels of technology flow, we construct a 'composite' stock of foreign R&D, defined below.[16]

$$IRD_j(t) = \sum_{c,\,k} \left(RD_{ck} P_{kj} S_{cj} \right)(t) \tag{9}$$

[15] We choose 1988 as the starting year of our analysis because it is the first year in which the data on the replacement value of capital are reported. We do not consider the year 1996 because, unlike in the previous years, the replacement value data in this year are not reported for individual asset categories—land, buildings, machinery, transport equipment and others. Instead, the replacement value of 'total' capital assets is reported. However, we prefer to calculate the total replacement value of capital after excluding land because foreign establishments in Indonesia are not allowed to own land and hence do not report data on land. We do not consider the period after 1996 in order to insulate our results from the effect of the financial and economic crisis of late 1997.

[16] Note that the specific channels of foreign technology flows are introduced in the inefficiency function.

where IRD_j is the international R&D stock resulting from technology flows available to all establishments in the Indonesian industry j; RD_{ck} is the R&D stock in sector k of partner-country c; P_{kj} is an element of the patent information flow matrix **P** (it captures the flow of sector k's R&D efforts to sector j. For more details, see Verspagen 1997); and S_{cj} is the technological congruence between sector j of Indonesia and the same sector of its partner country c. S_{cj} is derived by comparing the input coefficient vectors for sector j in the two countries:

$$S_{cj}(t) = \sum_j \min(A_{dj},\ A_{cj})(t); \quad 0 \leq S_{cj} \leq 1 \tag{10}$$

where, A_{dj} and A_{cj} are column vectors representing respectively the share in the column sum of the input coefficient vector for industry j of Indonesia *(d)* and the trading partner *(c)*. S_{cj} takes a value of 1 if the two sectors are perfectly similar and zero if they are perfectly dissimilar.

Given the fact that the R&D data we use are available only at a level of aggregation of 2-, 3- and in a few cases, 4-digit (ISIC, Rev. 2), IRD_j in the above equation corresponds to these levels. To generate *IRD* at the 5-digit level, we constructed similarity indices between the two sets of classifications, using their respective input coefficients vectors:

$$S_{hl}^{j}(t) = \sum \min(A_h^j,\ A_l^j)(t); \quad 0 \leq S_{hl}^{j} \leq 1 \tag{11}$$

where, A_h^j and A_l^j are the column vectors representing, respectively, the share in the column sum of the input coefficient vector of the Indonesian industry j at a higher level of aggregation of 2-, 3- or 4-digit, and at a lower level of aggregation of 5-digit. Appendix tables A.1 and A.2 provide some summary statistics of the variables and the industrial classification chosen, respectively.

5. Results

5.1. Results of the Stochastic Frontier Analysis

Table 1 reports the SFA estimation results at the establishment level for the 65 5-digit industry samples. For brevity, we do not report the estimation results for the establishment-dummies included in the inefficiency function. Table 2 provides a summary of these results.[17]

The results for the frontier production function show that the coefficients of both capital intensity (*k-l*) and the international R&D stock (*ird*), representing knowledge spillovers, have a positive sign in most industries. The estimated coefficients of capital intensities representing the slopes of the productivity frontiers are generally fairly small, however, and even statistically insignificant at the 10% level for 15 industries. This implies that it does not pay very much for establishments just to invest more, as is suggested by advocates of

[17] While techniques such as Dynamic Ordinary Least Square (DOLS) can address the problem of endogeneity in classical regression models, the SFA branch of econometrics is not advanced enough to tackle these issues. Nevertheless, endogeneity, especially of the foreign ownership variable, is an issue that needs to be addressed. We therefore experimented by using the lagged value of foreign ownership variable in the inefficiency equation of the SFA model. While the results display occasional differences in the magnitude of the coefficients, they do not alter the conclusions of the study. Therefore, we do not report estimation results based on the transformed foreign ownership variable.

accumulationist theories. Consequently, accumulation alone cannot be considered as an important source of productivity growth in Indonesian manufacturing.

The sensitivity of the frontier to increases in foreign R&D displays a mixed pattern. While the coefficient for this variable is significantly positive in 29 of the 65 industries studied, it is significantly negative in 22 industries. The best-practice establishments which reaped substantial gains as well those which suffered losses fall into broadly different categories of industries. We will discuss the inter-industry differences in the impact of this and other variables later in this subsection.

Our main interest lies in understanding the factors that cause deviations from the best-practice technology, i.e. in the results of the inefficiency model defined by equation (8). The estimate for the variance parameter γ *(gamma* in table 1 and 2*)* that corresponds to the estimated share of the inefficiency term in the variance of the composite error term has a positive sign in all industries, and is significant in most industries (47 industries). This suggests that inefficiency effects are likely to be significant in the analysis of the labour productivity of plants.

A negative sign for the coefficient of a variable in the inefficiency function indicates a negative impact of that variable on inefficiency (in other words, a positive impact on efficiency). Among all the absorptive capacity indicators, changes in labour quality (*LQual*) provide the most promising explanation for the changes relative to best-practice performance. Its coefficient has a negative sign in most industries (42 out of 65), with a statistical significance (at the 10% level) in 16 industries.

TABLE 1 *Explaining Labour Productivity: SFA Estimates for 65 5-digit (ISIC) Industries*[a]

Ind. No	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*	*16*
ISIC	*31151*	*31171*	*31179*	*31192*	*31241*	*31251*	*31272*	*31279*	*31281*	*31340*	*31410*	*31420*	*31440*	*33111*	*33112*	*33113*
Category	*RESOURCE-INTENSIVE INDUSTRIES*															
	Production Function															
Constant	20.814	-15.052	-8.812	-12.744	12.797	-2.270	4.489	-9.520	6.429	-8.088	1.574	8.199	27.620	4.015	5.125	16.346
	(6.008)*	(0.995)*	(1.828)*	(1.136)*	(2.942)*	(0.981)*	(17.781)	(1.729)*	(1.928)*	(1.879)*	(1.064)	(1.140)*	(5.883)*	(0.997)*	(0.998)*	(1.171)*
Cap/Lab	0.375	0.514	0.180	0.468	0.083	0.142	0.097	0.131	0.111	0.005	0.118	0.282	0.024	0.310	0.157	0.132
	(0.155)*	(0.013)*	(0.024)*	(0.037)*	(0.051)	(0.031)*	(0.094)	(0.053)*	(0.141)	(0.070)	(0.046)*	(0.061)*	(0.073)	(0.051)*	(0.065)*	(0.044)*
IRD	-0.847	1.281	1.087	1.119	-0.207	0.613	0.269	1.124	0.346	1.306	0.202	-0.061	-1.156	0.229	0.230	-0.493
	(0.395)*	(0.056)*	(0.191)*	(0.075)*	(0.192)	(0.063)*	(1.191)	(0.095)*	(0.181)*	(0.127)*	(0.068)*	(0.072)	(0.366)*	(0.075)*	(0.076)*	(0.082)*
	(mean) Inefficiency Function															
Constant	5.190	0.238	2.802	1.473	9.734	1.880	3.130	0.967	1.815	4.411	2.509	1.193	13.135	0.484	1.134	1.926
	(1.501)*	(0.502)	(0.139)*	(0.879)*	(0.837)*	(0.627)*	(1.245)*	(0.308)*	(0.843)*	(0.728)*	(0.381)*	(0.689)*	(2.805)*	(0.471)	(0.634)*	(0.279)*
Age	-0.858	0.029	-0.062	-0.327	-1.406	-0.231	-0.439	-0.001	0.025	-0.150	-0.311	-0.224	-2.846	-0.046	0.152	-0.042
	(0.474)*	(0.141)	(0.017)*	(0.246)	(0.167)*	(0.114)*	(0.609)	(0.099)	(0.284)	(0.127)	(0.078)*	(0.203)	(0.704)*	(0.142)	(0.204)	(0.069)
Foreign	0.583	-0.042	0.087	-1.624				0.917	-1.423	-1.697				0.547	-0.419	-6.817
	(1.320)	(0.311)	(0.353)	(0.838)*				(1.005)	(0.470)*	(0.439)*				(0.758)	(0.936)	(1.658)*
Access	-5.081	-1.714	-0.292	-1.346	-2.292	-2.564	-1.031	-2.179	0.822	0.009	-1.578	1.019	-0.405	-0.555	0.771	-0.323
	(5.026)	(0.903)*	(0.284)	(0.863)	(1.073)*	(1.190)*	(1.775)	(1.724)	(0.678)	(0.285)	(3.893)	(0.587)*	(1.491)	(0.991)	(1.144)	(0.208)
LQual	-0.018	0.386	-0.807	1.022	0.305	0.565	-0.428	-2.060	-0.444	-0.871	0.593	-0.070	-2.917	-0.488	-1.537	-2.147
	(0.400)	(0.879)	(0.333)*	(0.609)*	(0.375)	(0.634)	(2.318)	(0.536)*	(0.809)	(0.386)*	(0.847)	(0.864)	(0.908)*	(0.745)	(0.808)*	(0.638)*
Size	0.280	-0.332	0.040	0.042	0.450	0.141	0.221	0.051	-0.567	0.260	0.520	-0.251	0.278	-0.147	-0.078	-0.182
	(0.248)	(0.113)*	(0.050)	(0.220)	(0.098)*	(0.160)	(0.273)	(0.108)	(0.294)*	(0.144)*	(0.065)*	(0.139)*	(0.168)	(0.104)	(0.118)	(0.098)*
sigma-sq.	0.175	0.129	0.140	0.172	0.109	0.130	0.152	0.166	0.479	0.125	0.225	0.257	0.073	0.376	0.333	0.204
	(0.019)*	(0.010)*	(0.007)*	(0.045)*	(0.011)*	(0.010)*	(0.020)*	(0.016)*	(0.068)*	(0.016)*	(0.011)*	(0.033)*	(0.012)*	(0.045)*	(0.052)*	(0.018)*
gamma	1.000	0.558	0.002	0.600	1.000	0.259	1.000	0.044	1.000	0.008	0.000	0.115	0.158	0.465	0.060	0.081
	(0.000)*	(0.027)*	(0.293)	(0.087)*	(0.670)	(0.050)*	(0.000)*	(0.016)*	(0.000)*	(0.067)	(0.000)*	(0.016)*	(0.049)*	(0.062)*	(0.263)	(0.017)*
Establishments	24	104	73	21	28	83	15	26	18	25	137	33	10	69	40	30
Observ.	192	832	584	168	224	664	120	208	144	200	1096	264	80	552	320	240

(contd) TABLE 1 *Explaining Labour productivity: SFA Estimates for 65 5-digit (ISIC) Industries*[a]

Ind. No	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*	*31*
ISIC	*33114*	*33131*	*33211*	*35224*	*35511*	*35512*	*35523*	*35593*	*36111*	*36112*	*36321*	*32210*	*32312*	*32411*	*39090*
Category	*RESOURCE-INTENSIVE INDUSTRIES*											*LABOUR INT. INDUSTRIES*			
							Production Function								
Constant	4.559	4.154	15.234	-39.834	66.702	-50.514	-126.004	-149.796	-94.761	-44.240	-4.676	43.372	7.785	96.918	64.939
	(1.114)*	(11.332)	(2.325)*	(1.909)*	(212.454)	(0.998)*	(15.509)*	(1.008)*	(0.987)*	(1.009)*	(1.791)*	(2.677)*	(13.548)	(17.104)*	(0.998)*
Cap/Lab	0.150	0.377	0.200	0.091	-0.003	0.472	0.125	0.499	0.079	0.159	0.148	0.149	0.431	0.037	0.293
	(0.090)*	(0.272)	(0.031)*	(0.047)*	(0.078)	(0.084)*	(0.075)*	(0.058)*	(0.068)	(0.089)*	(0.035)*	(0.023)*	(0.131)*	(0.084)	(0.194)
IRD	0.245	0.186	-0.441	2.624	-3.328	3.347	8.206	9.435	5.873	3.018	0.748	-2.007	0.154	-5.097	-3.123
	(0.094)*	(0.906)	(0.153)*	(0.105)*	(12.839)	(0.078)*	(0.949)*	(0.069)*	(0.065)*	(0.085)*	(0.098)*	(0.153)*	(0.966)	(1.011)*	(0.104)*
							(mean) Inefficiency Function								
Constant	-0.115	3.164	3.529	4.435	8.123	0.460	3.122	0.308	0.358	0.469	2.908	2.379	4.168	2.676	-0.169
	(0.751)	(0.845)*	(0.429)*	(0.825)*	(5.102)	(1.305)	(0.894)*	(0.420)	(0.493)	(0.966)	(0.459)*	(0.187)*	(3.301)	(1.282)*	(1.682)
Age	-0.023	-0.106	-0.558	-0.089	-1.730	-0.140	-0.153	0.099	-0.058	-0.112	-0.312	-0.130	-0.158	0.416	-0.489
	(0.310)	(0.203)	(0.100)*	(0.141)	(1.758)	(0.199)	(0.219)	(0.070)	(0.172)	(0.342)	(0.082)*	(0.051)*	(0.295)	(0.422)	(0.279)*
Foreign	0.107		-0.058		-8.670		-0.183	-0.788	-0.019	-1.010	-0.798				
	(0.907)		(0.663)		(23.417)		(0.460)	(0.752)	(0.799)	(0.958)	(0.810)				
Access	-0.770	0.546	0.306	-1.525	-0.075	0.541	-0.646	1.002	-0.108	0.196	-0.200	0.090	-0.643	0.961	-1.086
	(0.946)	(1.360)	(0.350)	(0.702)*	(0.652)	(0.656)	(0.308)*	(0.349)*	(0.240)	(0.676)	(0.244)	(0.087)	(0.373)*	(0.336)*	(0.679)
LQual	-0.844	1.121	-0.919	-0.748	0.584	-0.235	-0.230	0.851	-0.589	1.111	0.037	-0.258	0.901	-2.229	0.053
	(1.066)	(1.288)	(0.380)*	(0.286)*	(0.739)	(0.853)	(0.364)	(0.398)*	(0.863)	(1.041)	(0.266)	(0.227)	(1.426)	(1.453)	(0.859)
Size	-0.556	0.306	0.117	0.795	-0.071	-0.094	0.290	-0.271	0.229	-0.186	0.404	0.007	-0.588	0.263	-0.329
	(0.316)*	(0.190)	(0.089)	(0.135)*	(0.417)	(0.320)	(0.177)	(0.085)*	(0.126)*	(0.184)	(0.089)*	(0.030)	(0.257)*	(0.176)	(0.716)
sigma-sq.	0.309	0.337	0.142	0.161	0.168	0.235	0.263	0.241	0.123	0.270	0.220	0.141	0.205	0.274	0.145
	(0.060)*	(0.054)*	(0.010)*	(0.019)*	(0.026)*	(0.080)*	(0.025)*	(0.024)*	(0.020)*	(0.053)*	(0.012)*	(0.005)*	(0.029)*	(0.011)*	(0.056)*
gamma	0.154	1.000	0.439	0.140	0.095	0.023	1.000	0.073	0.021	0.298	0.000	0.103	0.615	1.000	1.000
	(0.076)*	(0.414)*	(0.151)*	(0.029)*	(2.259)	(0.028)	(0.330)*	(0.017)*	(0.248)	(0.059)*	(0.000)	(0.016)*	(0.088)*	(0.000)*	(0.002)*
Establishments	13	11	69	19	10	11	33	27	12	11	107	182	13	17	10
Observ.	104	88	552	152	80	88	264	216	96	88	856	1456	104	136	80

(contd) TABLE 1 *Explaining Labour productivity: SFA Estimates for 65 5-digit (ISIC) Industries*[a]

Ind. No	*32*	*33*	*34*	*35*	*36*	*37*	*38*	*39*	*40*	*41*	*42*	*43*	*44*	*45*	*46*	*47*	*48*
ISIC	*32111*	*32114*	*32115*	*32116*	*32117*	*32121*	*32130*	*32190*	*34112*	*34113*	*34120*	*34200*	*35142*	*35210*	*35231*	*35232*	*35291*
Category								*SCALE INTENSIVE INDUSTRIES*									
								Production Function									
Constant	2.379	39.700	24.232	36.523	36.815	38.729	48.213	35.153	-17.000	16.791	11.845	16.160	-19.197	-12.618	-6.878	4.985	2.514
	(9.476)	(0.998)*	(1.102)*	(12.473)*	(266.69)	(8.129)*	(14.478)*	(16.705)*	(1.843)*	(5.690)*	(1.729)*	(0.945)*	(1.004)*	(12.584)	(17.735)	(4.011)	(1.013)*
Cap/Lab	0.022	0.357	0.302	0.491	0.086	0.093	0.221	-0.003	0.561	0.109	0.202	0.291	0.775	0.035	0.304	0.348	0.198
	(0.069)	(0.144)*	(0.056)*	(0.118)*	(0.858)	(0.055)*	(0.060)*	(0.082)	(0.043)*	(0.080)	(0.069)*	(0.029)*	(0.083)*	(0.071)	(0.084)*	(0.083)*	(0.097)*
IRD	0.445	-1.928	-1.017	-1.781	-1.616	-1.717	-2.079	-1.417	1.169	-0.406	-0.198	-0.507	1.113	1.156	0.850	0.099	0.398
	(0.545)	(0.094)*	(0.065)*	(0.750)*	(15.693)	(0.470)*	(0.711)*	(0.940)	(0.105)*	(0.313)	(0.093)*	(0.053)*	(0.062)*	(0.641)*	(0.855)	(0.208)	(0.077)*
								(mean) Inefficiency Function									
Constant	4.250	-0.395	-1.409	0.255	2.285	3.708	4.511	1.577	-1.242	0.417	6.852	1.173	0.231	3.203	5.702	3.270	1.706
	(1.449)*	(0.865)	(0.767)*	(1.595)	(38.602)	(0.602)*	(1.247)*	(0.841)*	(1.780)	(0.638)	(1.253)*	(0.417)*	(0.839)	(0.771)*	(2.164)*	(0.864)*	(1.171)
Age	-0.744	0.134	0.063	0.378	-0.175	-0.131	0.243	0.170	0.329	0.252	-1.443	-0.035	-0.029	-0.860	-0.556	-0.268	-0.100
	(0.395)*	(0.324)	(0.242)	(0.482)	(7.483)	(0.177)	(0.248)	(0.257)	(0.361)	(0.160)	(0.325)*	(0.109)	(0.232)	(0.240)*	(0.309)*	(0.179)	(0.277)
Foreign	-2.293	-0.211		-1.231		-0.467					0.985		1.177	-1.105		4.074	0.499
	(0.744)*	(0.998)		(0.993)		(0.316)					(0.780)		(0.993)	(0.481)*		(1.254)*	(0.448)
Access	-0.084	-0.599	0.452	-0.481	0.021	0.329	0.093	0.398	0.274	0.295	-4.338	0.124	-0.219	0.141	0.021	-0.118	-0.503
	(0.312)	(0.973)	(0.333)	(0.274)*	(2.107)	(0.238)	(0.340)	(0.288)	(0.672)	(0.443)	(0.924)*	(0.108)	(0.502)	(0.216)	(0.345)	(0.274)	(0.480)
LQual	3.626	-0.300	2.910	1.690	-1.555	-0.894	-1.680	-2.696	-2.819	-1.065	-0.693	0.099	1.389	-0.836	-2.462	-0.477	0.918
	(0.976)*	(0.991)	(1.107)*	(1.356)	(70.524)	(0.658)	(0.807)*	(0.908)*	(1.073)*	(0.724)	(0.694)	(0.345)	(0.783)*	(0.295)*	(0.592)*	(0.714)	(0.760)
Size	0.037	-0.463	0.102	-0.292	0.113	0.131	-0.049	-0.029	-0.433	-0.348	0.715	-0.092	-0.388	-0.045	0.369	0.130	0.087

	(0.191)	(0.098)*	(0.107)	(0.240)	(4.867)	(0.098)	(0.104)	(0.160)	(0.324)	(0.186)*	(0.211)*	(0.073)	(0.246)	(0.109)	(0.219)*	(0.161)	(0.287)
sigma-sq.	0.299	0.590	0.210	0.181	0.088	0.135	0.164	0.161	0.389	0.145	0.115	0.213	0.299	0.170	0.167	0.178	0.226
	(0.040)*	(0.886)	(0.029)*	(0.030)*	(0.793)	(0.011)*	(0.015)*	(0.019)*	(0.076)*	(0.023)*	(0.020)*	(0.010)*	(0.074)*	(0.015)*	(0.021)*	(0.026)*	(0.037)*
gamma	0.355	0.596	0.169	0.216	0.140	0.949	0.000	1.000	0.444	0.211	0.126	0.233	0.157	0.059	0.971	0.139	1.000
	(0.163)*	(0.205)*	(0.046)*	(0.262)	(8.629)	(0.481)*	(0.433)	(0.000)*	(0.149)*	(0.093)*	(0.062)*	(0.041)*	(0.181)	(0.022)*	(0.168)*	(0.504)	(0.000)*
Establishments	19	113	22	12	26	43	28	15	12	11	11	136	13	24	18	19	12
Observ.	152	904	176	96	208	344	224	120	96	88	88	1088	104	192	144	152	96

(contd) TABLE 1 *Explaining Labour productivity: SFA Estimates for 65 5-digit (ISIC) Industries*[a]

No	*49*	*50*	*51*	*52*	*53*	*54*	*55*	*56*	*57*	*58*	*59*	*60*	*61*	*62*	*63*	*64*
ISIC	*37103*	*38432*	*38433*	*38444*	*38113*	*38114*	*38120*	*38191*	*38193*	*38195*	*38199*	*38245*	*35222*	*35605*	*35606*	*35609*
Category	*SCALE INTENSIVE INDUSTRIES*				*DIFFERENTIATED INDUSTRIES*								*SCIENCE-BASED INDUSTRIES*			
								Production Function								
Constant	27.984	-6.181	20.534	-18.842	35.848	67.262	53.901	11.697	111.824	-45.939	65.418	-3.229	-13.149	-21.878	-11.255	-16.842
	(0.998)*	(6.774)	(1.038)*	(7.852)*	(1.062)*	(1.001)*	(18.279)*	(1.001)*	(2.058)*	(0.999)*	(52.529)	(1.629)*	(2.389)*	(11.509)*	(4.069)*	(37.311)
Cap/Lab	0.522	0.148	0.432	0.205	0.246	0.292	0.171	0.505	-0.181	0.496	0.130	0.256	0.156	0.217	0.177	0.219
	(0.155)*	(0.049)*	(0.118)*	(0.039)*	(0.079)*	(0.064)*	(0.149)	(0.096)*	(0.061)*	(0.118)*	(0.095)	(0.079)*	(0.060)*	(0.070)*	(0.041)*	(0.054)*
IRD	-1.192	0.820	-0.669	1.495	-1.525	-3.181	-2.206	-0.322	-5.195	2.679	-2.546	0.540	1.175	1.754	1.213	2.078
	(0.111)*	(0.359)*	(0.070)*	(0.196)*	(0.059)*	(0.061)*	(1.187)*	(0.072)*	(0.121)*	(0.081)*	(1.222)*	(0.088)*	(0.136)*	(0.697)*	(0.249)*	(1.970)
								(mean) Inefficiency Function								
Constant	1.849	5.200	1.619	6.203	0.134	-2.687	8.356	2.362	4.024	-0.582	11.007	2.921	2.399	1.081	3.900	10.780
	(0.854)*	(1.236)*	(1.908)	(0.866)*	(0.838)	(0.823)*	(5.114)	(0.955)*	(1.355)*	(0.974)	(28.559)	(1.065)*	(0.670)*	(0.577)*	(0.489)*	(4.865)*
Age	-0.130	-0.861	0.197	-1.517	-0.189	0.453	-0.508	-0.066	-0.570	0.300	-0.028	0.980	-0.115	-0.124	-0.451	-0.362
	(0.293)	(0.230)	(0.548)	(0.105)*	(0.193)	(0.246)*	(0.276)*	(0.296)	(0.272)*	(0.333)	(0.220)	(0.382)*	(0.155)	(0.115)	(0.100)*	(0.140)*
Foreign	-0.686		-2.807	-0.242		0.564		-0.367	-2.564	-1.414			2.882		-2.401	-0.516
	(0.788)		(1.148)*	(0.118)*		(0.725)		(0.843)	(2.629)	(0.848)*			(0.974)*		(1.134)*	(0.335)
Access	-0.384	-0.207	-0.411	-0.615	-0.016	0.557	0.902	-0.512	-0.303	0.784	-0.015	1.551	-0.091	0.491	0.148	-0.155
	(0.597)	(0.883)	(0.575)	(0.593)	(1.698)	(0.480)	(2.042)	(0.707)	(0.284)	(0.560)	(0.313)	(0.565)*	(0.219)	(0.243)*	(0.087)*	(0.154)

LQual	-1.718	-0.468	-1.657	-1.485	-0.236	-0.933	0.133	-1.278	-0.878	-0.163	-1.650	-4.763	-0.091	0.066	0.330	0.997	
	(0.931)*	(0.479)	(0.952)*	(9.983)	(0.991)	(0.941)	(0.693)	(0.970)	(1.234)	(0.934)	(1.245)	(1.063)*	(0.497)	(0.799)	(0.349)	(0.937)	(0
Size	-0.104	-0.061	0.246	0.366	-0.285	-0.770	0.535	0.291	-0.201	0.007	0.380	1.117	0.386	0.191	0.357	-0.196	-
	(0.305)	(0.116)	(0.316)	(0.394)	(0.177)	(0.201)*	(0.262)*	(0.185)	(0.217)	(0.357)	(0.235)	(0.331)*	(0.162)*	(0.141)	(0.101)*	(0.142)	(0
sigma-sq.	0.463	0.140	0.501	0.157	0.127	0.346	0.234	0.342	0.181	0.637	0.215	0.263	0.209	0.191	0.194	0.157	
	(0.128)*	(0.015)	(0.125)*	(0.075)*	(0.035)*	(0.067)*	(0.030)*	(0.068)*	(0.029)*	(0.180)*	(0.029)*	(0.038)*	(0.023)*	(0.019)*	(0.013)*	(0.016)*	(0.
gamma	1.000	0.977	0.809	0.104	0.340	0.465	0.582	0.296	0.547	0.432	0.394	0.718	0.251	0.148	0.370	0.000	
	(0.000)*	(0.082)	(0.049)*	(0.155)	(0.141)*	(0.086)*	(0.078)*	(0.085)*	(0.179)*	(0.169)*	(0.547)	(0.118)*	(0.065)*	(0.041)*	(0.172)*	(0.287)	(0
Establishments	18	22	18	19	12	22	15	15	13	14	13	12	55	24	67	26	
Observ.	144	176	144	152	96	176	120	120	104	112	104	96	440	192	536	208	

(contdx) TABLE 1 *Explaining Labour productivity: SFA Estimates for 65 5-digit (ISIC) Industries*[a]

Notes: [a] Standard errors are in parentheses; * significant at 10%.
(i) Cap/Lab-Capital-labour ratio; IRD-International R&D stock; Age-Age of the establishment; Foreign-Percentage of foreign ownership; Access-Access to spillover (share of imported intermediate inputs in total intermediate inputs); LQual-Labour quality (Proportion of non-production workers in total workers); Size- Logarithm of the total number of workers.
(ii) All variables except IRD are establishment level variables. IRD is measured at the industry level.
(iii) See appendix table A.2 for industry and industrial category definitions.
(iv) Blank cells corresponding to the variable *foreign* indicate the absence of foreign equity holding in the respective industries.

Foreign ownership (*foreign*) has a significantly negative coefficient in only 10 out of the 38 industries in which the shares held by foreign firms are positive in one or more establishments. It might well be that a linear specification of the inefficiency effects is not most appropriate here. Explorations to use multiple-regime econometrics (to identify critical values of the degree of foreign ownership), however, are beyond the scope of this paper; if only because such analyses have hardly been attempted in the SFA branch of econometrics. (For a good review of recently developed alternative approaches to SFA with panel data, see Green 2003).

We argued before that access to spillover (*access*) is likely to exert a major influence on the technical efficiency of establishments. However, this variable yielded a statistically significant negative coefficient in only eight industries. One reason for this result could be the narrowness of our measure of access to spillover as it does not consider the import of capital goods, import of disembodied technology, etc. Secondly, the import intensity in intermediate input use is rather low in most industries as may be required to generate sufficient within-establishment variations. An additional, and probably the most important, cause of very few significant results is the huge measurement errors that characterise data sets like ours. Although, we did ‘clean’ the data extensively (see appendix, section A.4), it is unlikely that this has removed all measurement errors.

The *age* variable appears to have demonstrated a favourable impact on assimilation. A statistically significant negative coefficient in 19 industries (as against a positively significant coefficient in just two industries) appears to suggest that an establishment’s ability to assimilate knowledge spillovers from abroad or from better performing domestic establishments increases with its experience. As argued by Klepper (2002), under competitive pressures, firms with greater experience are better positioned to enhancing their capabilities.

TABLE 2 *A Summary of the SFA Estimation Results*

Sign and significance	*Cap/ Lab*	*IRD*	*Age*	*Fore-ign*[*]	*Acce-ss*	*Lqu-al*	*Size*	*Gam-ma*
Total Sample (Number of Industries: 65)								
Positive & sig.	47	29	2	2	7	5	12	47
Negative & sig.	1	22	19	10	8	16	10	0
Positive & non-sig.	15	8	14	9	21	18	24	18
Negative & non-sig.	2	6	30	17	29	26	19	0
Total	65	65	65	38	65	65	65	65
Resource- intensive Industries (Number of Industries: 27)								
Positive & sig.	19	18	0	0	2	2	6	19
Negative & sig.	0	4	8	4	5	8	6	0
Positive & non-sig.	7	2	4	5	7	8	10	8
Negative & non-sig.	1	3	15	9	13	9	5	0
Total	27	27	27	18	27	27	27	27
Labour-intensive Industries (Number of Industries: 4)								
Positive & sig.	2	0	0	0	1	0	0	4
Negative & sig.	0	3	2	0	1	0	1	0
Positive & non-sig.	2	1	1	0	1	2	2	0
Negative & non-sig.	0	0	1	0	1	2	1	0
Total	4	4	4	0	4	4	4	4
Scale-intensive Industries (Number of Industries: 21)								
Positive & sig.	16	6	0	1	0	3	2	14
Negative & sig.	0	9	5	4	2	7	2	0
Positive & non-sig.	4	3	8	3	10	3	8	7
Negative & non-sig.	1	3	8	4	9	8	9	0
Total	21	21	21	12	21	21	21	21
Differentiated Industries (Number of Industries: 8)								
Positive & sig.	5	2	2	0	1	0	2	7
Negative & sig.	1	6	2	1	0	1	1	0
Positive & non-sig.	2	0	1	1	3	1	3	1
Negative & non-sig.	0	0	3	2	4	6	2	0
Total	8	8	8	4	8	8	8	8
Science-based Industries (Number of Industries: 5)								
Positive & sig.	5	3	0	1	3	0	2	3
Negative & sig.	0	0	2	1	0	0	0	0
Positive & non-sig.	0	2	0	0	0	4	1	2
Negative & non-sig.	0	0	3	2	2	1	2	0
Total	5	5	5	4	5	5	5	5

Notes: See appendix table A.1 for industry and industrial category definitions.

Our period of analysis covers the export-oriented phase—the more competitive phase—of industrialisation in Indonesia. We may therefore conclude that establishments which have been in operation for a longer period of time have been more successful in enhancing their technological and managerial capabilities, and therefore in meeting the challenges of increased competition. We will show more evidence of this later when we compare the results across different categories of industries.

The final variable to be discussed is *size*, which displays considerable inter-industry variations in its influence. While a statistically significant impact of this variable on assimilation was adverse in 12 industries, it was favourable in 10 cases.

To gain insights into inter-industry differences in productivity dynamics, we have classified industries into five categories: resource-intensive, labour-intensive, scale-intensive, differentiated, and science-based industries (classification based on OECD 1987). While the results for the 65 industries in general appear to hold largely true across these five categories, a few significant differences are worth noting. First, we noted earlier that the contributions of international R&D variable displayed a mixed pattern, with the number of statistically significant positive contributions slightly higher than the number of statistically significant negative contributions. The favourable effect of foreign R&D was particularly pronounced in two categories of industries: the resource-intensive and science-based industries. Foreign R&D was a significant contributor in 18 out of the 27 industries in the former category (which account for the majority of industries in the total sample) and in three out of the five industries in the latter category. The adverse effect of the international R&D variable was confined mainly to industries which were in the three remaining categories: the scale-intensive, differentiated and labour-intensive categories.

It may be noted that the resource-intensive and science-based industries played a central role in the export-orientation drive of the late 1980s; the resulting increase in competitive pressure and external contacts may have been responsible for the greater positive impact of technology spillovers in these industries than in others. The scale-intensive and differentiated industries (which together account for the majority of the industries with a statistically significant negative coefficient for the foreign R&D variable), on the other hand, were the most important beneficiaries of the import-substituting regime that prevailed until the mid-1980s. Thereafter, given a lack of policy-thrust on exports and the resulting failure to effect technological upgrading, imports could have replaced some of the domestic production (see Jacob (2006), chapter 2 for some evidence on this). Assuming that the decline in domestic production was not matched by a reduction in domestic employment, the net effect would be a decline in labour productivity. To sum up our explanation of negative effect of foreign R&D spillovers in these categories of industries, domestic competitiveness stemming from foreign R&D spillovers as well as domestic technological effort failed to counter the R&D-induced competitiveness of imports from trading partners. Needless to add, this is an admittedly speculative proposition which, however, deserves a closer scrutiny in future research.

Another notable difference in the results across the industrial categories is with respect to the age variable. While its contribution was favourable in general, establishments belonging to the resource-intensive industries appear to have been greater beneficiaries of experience compared to those in the other industries. We noted earlier that experience has a favourable impact when the price-cost margin is low. As mentioned in the previous paragraph, the resource-intensive industries were subjected to a greater degree of external competition than the industries in the other categories; this might have caused greater relevance for experience in the former category of industries.

Labour quality in general was a favourable contributor to production efficiency; however, in the science-based category its coefficient has a positive sign, although not significant, in four out of the five industries. The latter result underscores the fact that the science-based industries in Indonesia engage in low-skilled, low-value added activities. Finally, and not surprisingly, the size variable generated a favourable impact, against the general trend, in many of the scale-intensive industries. As Pavitt (1984) notes, firms that are bigger in these industries are able to benefit from static scale economies of production.

5.2. Results of the Decomposition Analysis

The discussion so far has revealed that changes in deviations from best-practice (due to establishment-specific factors) are a significant determinant of an establishment's labour productivity growth. In the following section we extend these results by decomposing labour productivity growth into the three components introduced in section 3.1: growth resulting from shifts in the frontier of an industry's technology (innovation), growth resulting from increasing capital intensity (potential), and efficiency gains (or losses) relative to the frontier (assimilation). The latter is distinguished further into assimilation effect that is explained by the variables of the inefficiency function, and that remains unexplained.

We decomposed establishment-level labour productivity growth during the period 1988-95 in each of the 65 industries considered, based on equation (1). We then calculated their industry-average using the following transformation:

$$x = \frac{\sum_{i=1}^{n}(w_i x_i)}{n} \tag{12}$$

where x represents labour productivity growth and each of its four components—explained assimilation, unexplained assimilation, innovation and creating potential; the subscript i stands for establishments; n is the total number of establishments in the 5-digit industry; and w_i is the employment-share weight used to arrive at the industry-level figures. It is defined as

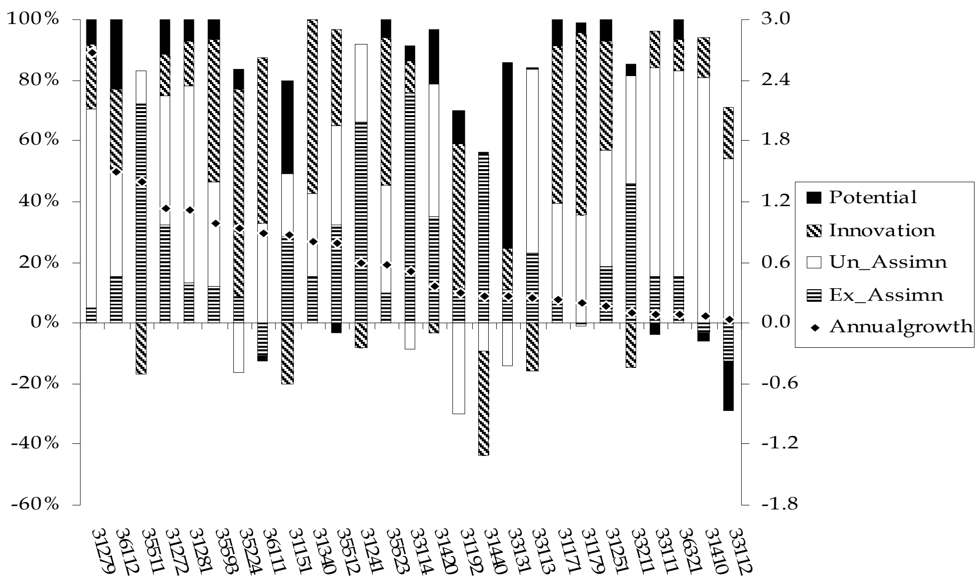
$$w_i = \left(l_i^{1988} l_i^{1995}\right)^{0.5} \tag{13}$$

where l_i is the employment share of establishment i in the 5-digit industry, and the superscripts 1988 and 1995 correspond to the initial and final years.[18]

Figures 2 to 6 show the decompositions of average labour productivity growth rates across the five industrial categories during the period 1988-95. The secondary Y-axis shows the compound annual average percentage growth in labour productivity and the primary Y-axis shows the contribution of the four components to the (period) labour productivity growth. These results are also provided in appendix table A.3, which also reports the period growth rates of labour productivity.

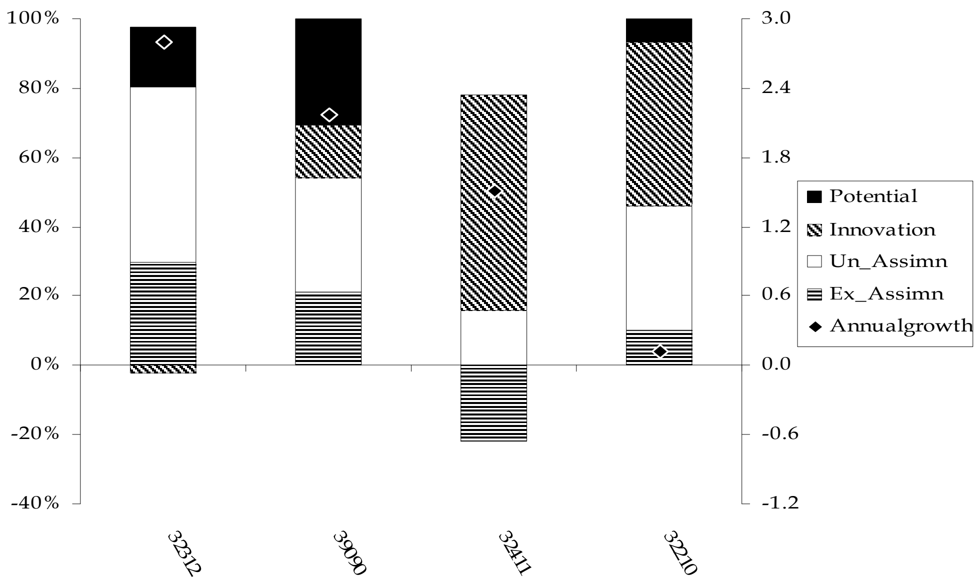
FIGURE 2 *Decomposition of Productivity Growth: Resource- intensive Industries*

[18] Prior to deriving the industry-average, the multiplicative components of the decomposition equation were transformed, by taking their logarithms, into additive components.



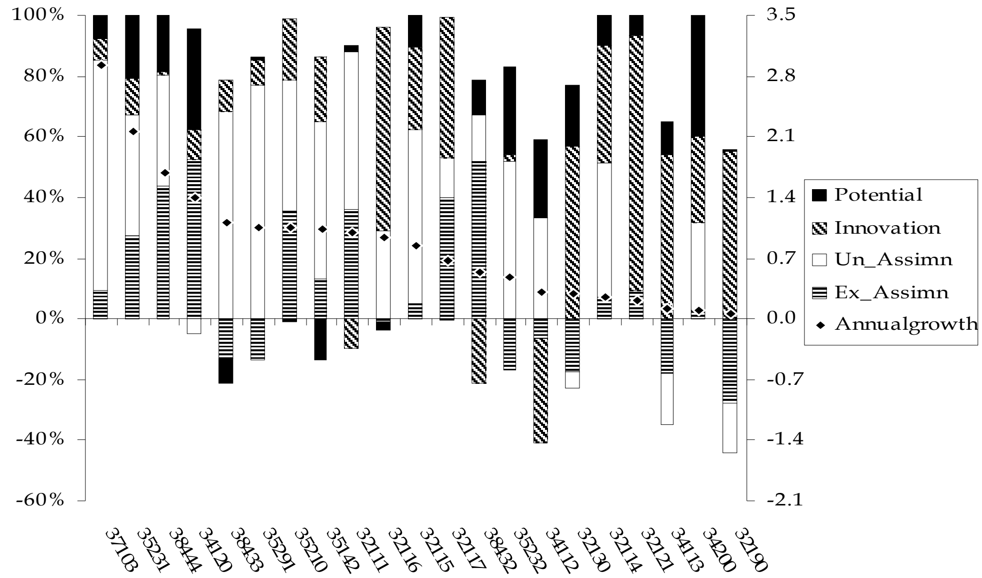
Note: Industry (ISIC 5-digit) on X-axis, compound annual percentage growth rate of labour productivity on secondary Y-axis, and contribution of four components to the (period) growth rate of labour productivity on primary Y-axis. See appendix table A.2 for industry and industrial category definitions.

FIGURE 3 *Decomposition of Productivity Growth: Labour-intensive Industries*



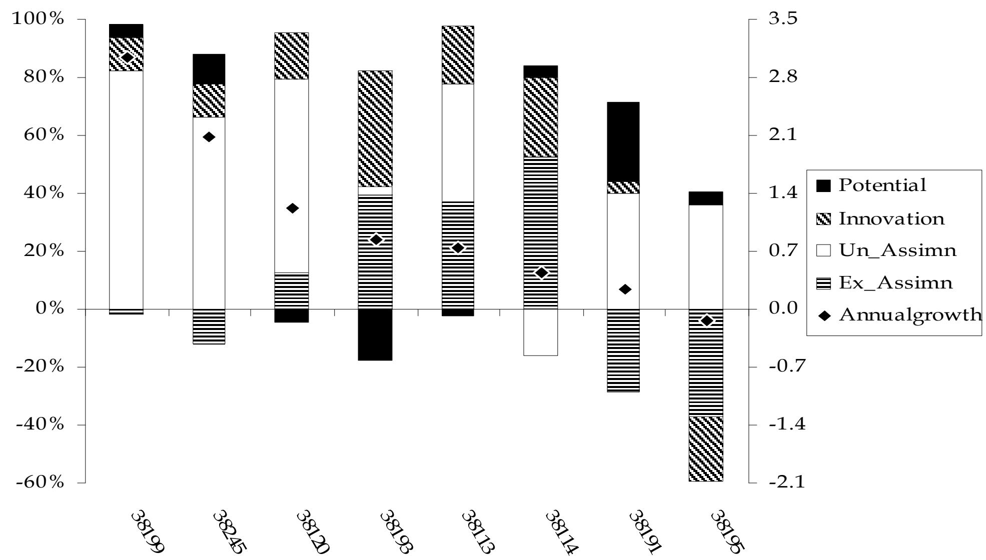
Note: See notes for figure 2.

FIGURE 4 *Decomposition of Productivity Growth: Scale-intensive Industries*



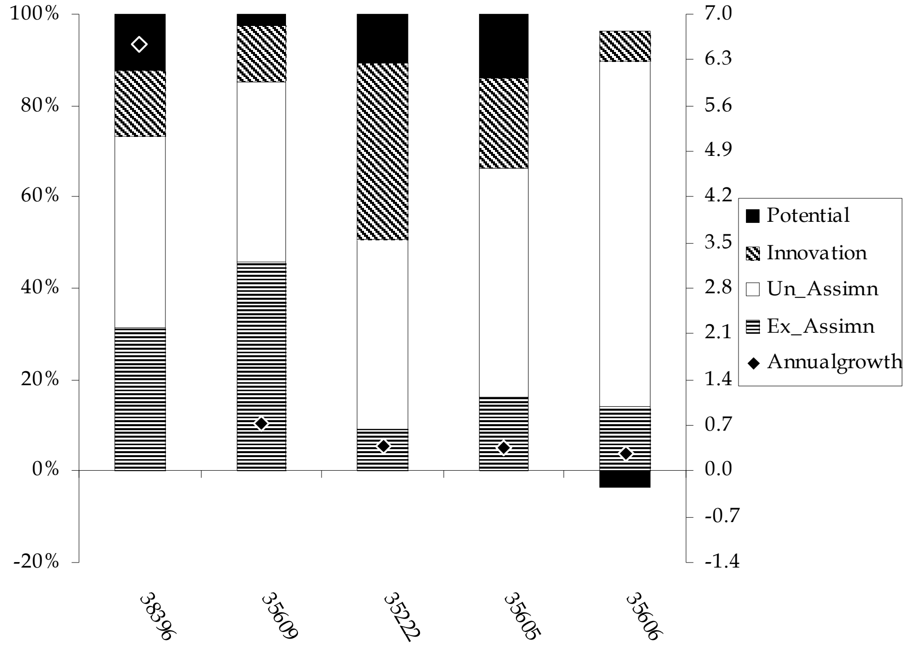
Note: See notes for figure 2.

FIGURE 5 *Decomposition of Productivity Growth: Differentiated Industries*



Note: See notes for figure 2.

FIGURE 6 *Decomposition of Productivity Growth: Science-based Industries*



Note: See notes for figure 2.

All industries (with the single exception of metal pipe & pipe fitting, ISIC code: 38195) experienced a positive growth in labour productivity during this period, with important inter-industry variations as may be expected of a heterogeneous group of industries. In majority of the industries, productivity growth resulted from a combination of assimilation (both explained and unexplained) and innovation. Among the three, unexplained assimilation (U_Assimn) was the single most important contributor to productivity growth (in about two-fifth of the industries), followed by innovation (in about one-fourth) and to a lesser extent explained assimilation (E_Assimn) (in about one-seventh of the industries).

The contribution of creating spillover potential was very limited in most industries. This result is mainly due to the flat shapes of the estimated frontiers. Increasing capital intensity does hardly contribute to a higher potential labour productivity. In other words, learning- or assimilation-potentials remained more or less stagnant.

Looking across the five categories of industries, assimilation effect appears to have made the strongest impact in the resource-intensive and science-based sectors. The same reasoning we put forward earlier for the importance of foreign technology spillovers in these industries—that these industries spearheaded the export-orientation drive of the late-1980s—could be attributed to this. Another significant difference across the industrial categories pertains to the effect of creating potential. While the importance of this factor was low in general, it made important, though not the highest, contribution in many of the scale-intensive industries.

The decomposition results discussed above have underscored the case for explanations of productivity growth in developing countries that are based on the theories of appropriate technology and assimilation. Due perhaps to the dualistic character of Indonesian manufacturing, productivity gains through upgrading into machineries with newer technologies was important in a few industries.[19] However, in many industries, increases in physical-capital investment *per se* barely contributed to substantial productivity gains. In fact, the assimilation of knowledge, corresponding to existing technologies, was of much greater importance for labour productivity growth. The low impact of physical-capital upgrading might also reflect the failure to enhance absorptive capacity in tune with the increase in the 'target' productivity level (see footnote 10).

6. Conclusions and Future Research

In this paper, we examined the effect of foreign technology spillovers on labour productivity growth in the Indonesian manufacturing sector for the period 1988-95. Our approach differed from the existing studies on technology spillovers in two important respects: first, we adopted an SFA approach wherein a distinction was made between establishments operating at the *frontier* labour productivity levels and those operating below this frontier; and second, drawing on the SFA results, we carried out a decomposition of industry-average labour productivity growth in the spirit of the assimilationist and appropriate technology theories of catching up and falling behind.

In our SFA model, technological change (shifts in frontier labour productivity) was linked to foreign technology spillovers at different capital-labour ratios, and the failure to attain the industry-best-practice productivity levels was linked to a set of establishment-specific absorptive capacity indicators.

Foreign R&D's contribution in upwardly shifting the productivity frontier was mixed. The creation of spillover potential (by investing to use more capital-intensive technologies) did not in general contribute to labour productivity growth. Thus, shifting to higher capital intensities *per se* do not imply more potential spillovers to benefit from. This finding is clearly at odds with the major assumptions underlying the accumulationist theories of growth.

Assimilation (movements towards the frontier) did play an important role. We could distinguish between two kinds of assimilation effects. The first type is that which is explained by our absorptive capacity indicators, such as labour quality, access to technology spillovers, degree of foreign ownership, experience and establishment size. For many industries, the estimation results underline the importance of building absorptive capacity for assimilating technology spillovers—from abroad and from better performing domestic establishments that operate similar technology. In a quantitative sense, however, these effects were often dwarfed by the second kind of assimilation effects. This unexplained assimilation effects were very big and dominated the composite effect.

The importance of unexplained assimilation is worrisome on the one hand, in the sense that we cannot explain much. On the other hand, it confirms our feeling that much of the heterogeneity among establishments is not captured by survey-based data sets. Our absorptive capacity indicators are rough ones, and are subject to considerable measurement errors.

The sizeable number of 5-digit industries considered enabled us to gain some important insights into inter-industry differences in productivity growth dynamics. Among these, the

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[19] In this context, we may note the emphasis placed on labour-intensive production in Indonesia during the export-orientation drive beginning the late 1980s. Although labour-intensive production will result in lower labour productivity, it could well result in higher total factor productivity (TFP) at a given point in time. The thrust on exploiting the domestic comparative advantage of cheap labour in the short term, however, is at odds with the need to increase capital intensity to profit from spillovers in the longer term. Conversely, capital intensification can be disadvantageous if it runs too much counter to the short run comparative advantage. Reconciling the short-term and long-term goals is therefore an important policy challenge.

most notable was the uniquely significant effect of foreign R&D in industries that were at the forefront of the export-orientation drive of the late 1980s—the resource-intensive and science-based industries. In the former category, a majority of industries also experienced a favourable assimilation effect on account of superior learning efforts by more experienced establishments.

From a policy point of view, the results suggest that enhancing absorptive capacity is a major precondition for catching up, *inter alia* through technology spillovers, and, particularly in the context of Indonesian manufacturing, by overcoming the dualities in production processes. Of course, more in-depth case studies (e.g. Pack 1987; van Dijk 2005) offer greater opportunities for assessing the importance of foreign technology and differences in absorptive capacity. Studies like ours can play a useful role in investigating the extent to which case study results can be generalised.

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A. Appendix: Data and Sample Selection

A.1.Combining the Backcast and Statistik Industri (SI) Data Sets

The SI data is based on annual surveys conducted on establishments in the medium and large manufacturing sector by the central statistics agency of Indonesia (*badan pusat statistik*, BPS). In earlier surveys, especially those before 1985, a large number of establishments that were in operation were not accounted for. To correct for this, BPS initiated a new manufacturing survey in 1993 to collect information on establishments that were not covered by SI from 1975 onwards (Jammal 1993). The additional survey, called the *backcast* survey, however, is limited to information on only key variables such as output, value added and labour (in contrast to the detailed coverage of establishment-level variables in SI). To profit from variables additionally reported in SI (among which data on import of material and foreign ownership are of relevance for this paper) on the one hand, and from the greater reliability of key variables—output, value added and labour—reported in backcast on the other, we merged the two data sets. In both the data sets, each establishment is given a unique identifier. Across the two data sets, however, different identifiers have been assigned to the *same* establishments, in many cases. In view of this problem, first we identified and merged establishments with identical output, value added and labour, and second, for the remaining un-merged observations, we used the establishment-identification codes. The observations that did not merge after the two above steps were dropped from the sample.

A.2. Choice of the Sample Period

As noted above, until the mid-1980s, the SI manufacturing survey suffered from considerable under-representation of the medium and large manufacturing industry. This is discernable, in addition to by comparing it with the backcast data, from a jump in the number of establishments of more than 50% between 1984 and 1985 (resulting from the 'discovery of new establishments' by the BPS). This has been less of a problem after 1985, and since the post-1985 period covers a large part of the Indonesian industrialisation, and due to the availability of data on replacement value of capital only from 1988 we choose 1988 as the starting year of analysis. For 1996 only the replacement value as total of all assets—land, building, machinery, transport equipment and others—is available, while for the previous years replacement value for each asset category is available. In calculating the total replacement value from 1988 to 1995, we do not consider the asset category land, because foreign firms in Indonesia are not allowed to own land.

A.3. Generating Unique Observations

A key problem with both the backcast and SI data sets is the presence of duplicate observations, and even duplicate establishment-identification codes. Most of these result from the BPS practice of generating data for establishments that do not report data for some years based on the data of establishments with 'similar' characteristics. While this is justifiable for a more accurate representation of manufacturing at the industry level, this may distort analyses at the establishment level. We therefore removed observations with either repeated values for the variables output, value-added and labour, or repeated establishment identification codes (in any given year). While generating unique observations, care is taken to retain observations that possessed information on other variables. We also identified and removed 81 establishments for which no identification codes were assigned. At the end of this stage we were left with a sample of 161,932 unique observations off a total of 168, 400 observations for the period 1988-95. This was reduced further to 119,597 when 5-digit industries which did not possess at least 10 establishments a year, and without a positive intermediate input import every year were dropped.

A.4. Selection of Establishments and Removing Outliers

In addition to removing duplicate observations, we have made adjustments for outliers and other errors in the data. In what follows we discuss the corrections made for each variable.

Age

The SI data provide information on the year of inception for each establishment. For some establishments the data reported show variations over time, however. To correct this we retained the year of inception that is reported for the maximum number of years. For some establishments, however, the year of inception reported was more recent than the earliest year for which information about them was recoded in the full data set (1975-96). In such cases, we considered the earliest recorded year of an establishment as its year of inception.

Foreign Ownership

The foreign ownership variable we use in the study shows the percentage share of foreign ownership in a manufacturing establishment. Instances of erroneous reporting falls roughly into two categories: 1. positive values in the border years (not necessarily the first and last years) coupled with zeros in the intervening years (e.g. 50 **0 0 0** 50), 2. unrealistically different value for a given year (two times as high or half as less) compared to the values reported in the preceding and following years (e.g. 15 **45** 15 or 65 **5** 65). In both cases, we used interpolation to correct the series.

Other Variables

For the remaining variables used in the study—output, replacement value of capital, employment (total number of employees, and number of non-production workers), value added and intermediate inputs (total as well as imported)—the problem is one of unrealistic rises or falls over time. To correct for this, we used interpolation to replace such values within a window of two consecutive years. We adopted carefully constructed criteria to identify errors in the series for different sets of variables.

For the output and labour variables, we considered as erroneous a rise of either 6 times or more or a fall of .17 or less in any year compared to the previous year. Correcting for this led to the elimination of 6,695 observations, leaving 112,902 observations in the sample.

For value added, replacement value of capital and intermediate inputs, identification of errors was carried out in relation to their shares in output; for imported intermediate inputs in relation to their share in total intermediate input use; and for non-production workers in relation to their share in total employment. Removal of outliers in the value added variable reduced the sample to 111,479 observations, that in intermediate inputs to 105,577 observations, and that in non-production workers to 97,138 observations.

Finally we generated a balanced sample for the period 1988-95 consisting of 65 5-digit industries (each with at least 10 establishments or more, and with a positive intermediate input import every year). Appendix table A.1 presents the summary statistics for these industries, which together consist of 17,520 observations. The sizeable reduction in the number of establishments is indeed the cost we paid for maintaining a balanced sample of establishments in each industry.

A.5. Price Indices

We represent our data in 1990 Purchasing Power Parity dollars. We used three price indices for deflating the variables. For value added and output, we used the detailed commodity price index data made available to us by the BPS. For the replacement value of capital we used a price index of non-residential and residential building for building; a price index of imported machinery for machinery and equipment; and a price index of imported transport equipment for vehicles and for others. For the OECD R&D data, we used implicit price indices derived from the current and constant price value added series for each industry.

TABLE A.1 *Summary Statistics of 65 5-digit ISIC Industries*
(means, standard deviations in brackets)

No.	*ISIC*	*Val/ Lab*	*Cap/ Lab*	*IRD*	*Age*	*Foreign*	*Access*	*LQual*	*Size*
RESOURCE-INTENSIVE INDUSTRIES									
1	31151	8.878	9.141	15.751	2.973	0.025	0.001	0.266	-2.911
		(1.151)	(1.374)	(0.159)	(0.508)	(0.120)	(0.004)	(0.171)	(1.037)
2	31171	7.626	7.306	15.476	2.650	0.005	0.015	0.066	-3.117
		(0.695)	(1.130)	(0.158)	(0.620)	(0.055)	(0.045)	(0.060)	(0.671)
3	31179	8.116	8.202	15.984	2.684	0.011	0.033	0.138	-2.739
		(0.816)	(1.159)	(0.158)	(0.690)	(0.098)	(0.123)	(0.109)	(0.890)
4	31192	7.992	8.100	15.763	2.939	0.035	0.057	0.138	-2.636
		(0.921)	(1.282)	(0.159)	(0.713)	(0.159)	(0.091)	(0.139)	(0.933)
5	31241	8.383	8.171	15.385	3.214		0.011	0.196	-3.043
		(0.630)	(0.895)	(0.159)	(0.779)		(0.038)	(0.112)	(0.838)
6	31251	7.649	7.126	15.602	2.555		0.000	0.069	-3.334
		(0.550)	(0.918)	(0.158)	(0.580)		(0.005)	(0.119)	(0.442)
7	31272	7.917	7.687	15.984	2.810		0.020	0.171	-3.177
		(0.745)	(1.040)	(0.159)	(0.840)		(0.073)	(0.189)	(0.636)
8	31279	8.077	7.577	15.977	2.375	0.011	0.030	0.130	-3.070
		(0.887)	(1.283)	(0.159)	(0.608)	(0.058)	(0.149)	(0.109)	(0.772)
9	31281	9.981	9.981	15.912	2.207	0.080	0.123	0.308	-2.382
		(1.200)	(1.111)	(0.159)	(0.541)	(0.221)	(0.197)	(0.154)	(0.736)
10	31340	8.663	8.838	15.730	2.770	0.078	0.075	0.287	-2.804
		(1.442)	(1.667)	(0.159)	(0.739)	(0.224)	(0.217)	(0.215)	(1.073)
11	31410	6.375	6.820	15.791	2.854		0.002	0.022	-3.200
		(0.916)	(0.744)	(0.158)	(0.617)		(0.017)	(0.052)	(0.514)
12	31420	8.457	7.416	15.860	2.981		0.040	0.116	-1.306
		(1.016)	(1.181)	(0.159)	(0.692)		(0.127)	(0.106)	(1.204)
13	31440	7.542	6.800	15.791	3.357		0.094	0.099	-2.064
		(0.819)	(0.931)	(0.159)	(0.386)		(0.224)	(0.079)	(0.620)
14	33111	9.220	8.997	14.479	2.389	0.019	0.010	0.184	-2.250
		(0.870)	(1.093)	(0.099)	(0.614)	(0.122)	(0.063)	(0.117)	(1.225)
15	33112	9.151	9.353	15.165	2.234	0.012	0.005	0.185	-1.855
		(0.855)	(1.095)	(0.099)	(0.591)	(0.076)	(0.021)	(0.124)	(1.204)
16	33113	9.484	9.766	15.139	2.418	0.044	0.028	0.125	0.073
		(0.841)	(1.169)	(0.099)	(0.470)	(0.133)	(0.085)	(0.083)	(1.177)
17	33114	9.640	10.136	16.018	2.282	0.043	0.039	0.147	-0.285
		(0.713)	(0.937)	(0.099)	(0.582)	(0.133)	(0.092)	(0.092)	(0.987)
18	33131	8.519	8.659	15.139	2.188		0.028	0.090	-1.376
		(0.835)	(0.715)	(0.099)	(0.834)		(0.070)	(0.074)	(0.872)
19	33211	8.443	8.019	15.371	2.406	0.011	0.017	0.111	-2.770
		(0.701)	(1.369)	(0.099)	(0.600)	(0.081)	(0.076)	(0.116)	(1.031)
20	35224	8.252	8.269	18.375	2.912		0.080	0.204	-2.352
		(0.815)	(0.954)	(0.111)	(0.588)		(0.184)	(0.140)	(1.245)
21	35511	9.087	9.234	16.597	3.084	0.136	0.312	0.145	-1.188
		(1.215)	(1.495)	(0.017)	(0.525)	(0.284)	(0.203)	(0.101)	(1.005)
22	35512	9.100	9.226	16.597	2.354		0.247	0.304	-2.701

		(0.963)	(1.106)	(0.017)	(0.643)		(0.375)	(0.149)	(0.862)
23	35523	9.287	9.248	16.661	2.866	0.149	0.085	0.194	-1.804
		(0.985)	(0.969)	(0.017)	(0.531)	(0.354)	(0.227)	(0.135)	(0.902)
24	35593	8.173	8.301	16.430	2.573	0.048	0.134	0.113	-2.581
		(0.970)	(0.978)	(0.017)	(0.653)	(0.175)	(0.232)	(0.090)	(1.181)
25	36111	8.379	8.464	17.534	2.290	0.067	0.511	0.096	-1.210
		(0.514)	(0.831)	(0.024)	(0.653)	(0.222)	(0.366)	(0.068)	(1.430)
26	36112	9.339	10.106	17.493	2.363	0.036	0.403	0.161	-1.152
		(0.888)	(1.047)	(0.024)	(0.368)	(0.116)	(0.303)	(0.083)	(0.802)
27	36321	8.245	8.369	17.701	2.643	0.010	0.034	0.163	-3.087
		(0.935)	(1.082)	(0.023)	(0.574)	(0.075)	(0.098)	(0.122)	(0.775)
LABOUR INTENSIVE INDUSTRIES									
28	32210	8.097	7.675	17.327	2.578		0.076	0.069	-2.670
		(0.817)	(1.226)	(0.081)	(0.657)		(0.199)	(0.073)	(1.171)
29	32312	9.060	9.196	16.439	2.861		0.071	0.145	-2.553
		(0.885)	(0.962)	(0.081)	(0.983)		(0.163)	(0.082)	(0.688)
30	32411	8.527	8.376	16.992	2.449		0.094	0.137	-2.477
		(0.827)	(0.806)	(0.081)	(0.653)		(0.235)	(0.090)	(1.058)
31	39090	8.315	8.268	18.291	2.497		0.149	0.163	-3.413
		(0.935)	(1.233)	(0.029)	(0.787)		(0.306)	(0.141)	(0.306)
SCALE INTENSIVE INDUSTRIES									
32	32111	9.323	9.850	17.557	2.875	0.175	0.309	0.186	-0.893
		(0.843)	(1.227)	(0.081)	(0.511)	(0.317)	(0.393)	(0.100)	(1.374)
33	32114	8.509	8.756	17.348	2.742	0.012	0.063	0.108	-1.592
		(0.935)	(1.261)	(0.081)	(0.618)	(0.091)	(0.183)	(0.083)	(1.250)
34	32115	8.567	9.043	17.327	2.678		0.103	0.126	-1.988
		(0.837)	(1.155)	(0.081)	(0.416)		(0.239)	(0.099)	(1.130)
35	32116	8.445	8.900	17.146	3.026	0.054	0.159	0.119	-1.520
		(1.099)	(1.023)	(0.081)	(0.494)	(0.181)	(0.316)	(0.054)	(1.093)
36	32117	7.902	7.643	17.557	2.781		0.202	0.067	-3.132
		(0.616)	(1.348)	(0.081)	(0.652)		(0.254)	(0.102)	(0.668)
37	32121	8.010	7.954	17.146	2.791	0.006	0.047	0.095	-2.535
		(0.721)	(1.204)	(0.081)	(0.675)	(0.076)	(0.141)	(0.101)	(0.937)
38	32130	8.470	8.398	17.673	2.585		0.042	0.108	-2.238
		(0.819)	(1.040)	(0.081)	(0.578)		(0.177)	(0.061)	(0.923)
39	32190	8.422	8.898	17.673	2.299		0.110	0.142	-2.064
		(0.638)	(1.008)	(0.081)	(0.620)		(0.279)	(0.083)	(1.103)
40	34112	9.122	9.731	18.340	2.795		0.259	0.200	-1.269
		(1.478)	(2.145)	(0.144)	(0.578)		(0.316)	(0.154)	(1.471)
41	34113	8.889	9.491	18.340	2.370		0.117	0.179	-1.880
		(0.985)	(1.173)	(0.144)	(0.753)		(0.216)	(0.100)	(0.943)
42	34120	9.408	9.753	18.260	2.699	0.009	0.059	0.179	-1.715
		(0.789)	(0.944)	(0.144)	(0.478)	(0.060)	(0.131)	(0.097)	(1.004)
43	34200	8.727	9.219	18.317	2.875		0.080	0.234	-2.772
		(0.856)	(1.119)	(0.143)	(0.612)		(0.162)	(0.158)	(0.957)
44	35142	9.037	9.195	19.590	2.365	0.119	0.372	0.245	-2.117
		(1.219)	(1.337)	(0.075)	(0.716)	(0.230)	(0.300)	(0.229)	(1.058)
45	35210	8.912	8.696	19.633	2.611	0.035	0.245	0.231	-2.681
		(1.002)	(0.934)	(0.075)	(0.436)	(0.146)	(0.285)	(0.154)	(0.857)
46	35231	8.317	8.171	19.432	2.753		0.215	0.218	-2.423

		(0.814)	(1.263)	(0.075)	(0.566)		(0.314)	(0.166)	(1.252)
47	35232	8.791	8.733	19.309	2.472	0.043	0.465	0.255	-2.436
		(0.763)	(0.998)	(0.075)	(0.614)	(0.136)	(0.405)	(0.147)	(1.113)
48	35291	10.326	10.696	19.309	2.419	0.074	0.509	0.405	-2.299
		(1.504)	(1.802)	(0.075)	(0.573)	(0.184)	(0.338)	(0.182)	(0.674)
49	37103	10.280	10.224	16.842	2.569	0.076	0.215	0.258	-1.665
		(1.225)	(1.148)	(0.035)	(0.501)	(0.213)	(0.287)	(0.121)	(0.690)
50	38432	8.743	8.714	20.305	2.504		0.013	0.178	-2.520
		(0.678)	(1.078)	(0.137)	(0.484)		(0.051)	(0.103)	(0.808)
51	38433	9.775	9.895	20.305	2.348	0.043	0.411	0.196	-1.577
		(1.121)	(1.285)	(0.137)	(0.508)	(0.157)	(0.406)	(0.115)	(0.848)
52	38444	8.345	8.529	17.897	2.671	0.032	0.109	0.134	-2.496
		(0.835)	(1.021)	(0.038)	(0.328)	(0.134)	(0.280)	(0.087)	(0.996)
DIFFERENTIATED INDUSTRIES									
53	38113	8.097	7.883	19.218	2.505		0.018	0.095	-2.950
		(0.449)	(0.576)	(0.050)	(0.575)		(0.042)	(0.052)	(0.856)
54	38114	8.499	8.518	19.014	2.459	0.076	0.383	0.108	-2.168
		(0.946)	(1.109)	(0.050)	(0.580)	(0.193)	(0.427)	(0.084)	(1.341)
55	38120	8.501	8.326	19.090	2.398		0.010	0.210	-2.380
		(0.865)	(1.190)	(0.050)	(0.519)		(0.039)	(0.140)	(0.921)
56	38191	9.238	9.318	19.014	2.633	0.050	0.082	0.164	-2.594
		(1.031)	(1.073)	(0.050)	(0.496)	(0.187)	(0.181)	(0.096)	(0.875)
57	38193	8.861	9.199	19.090	2.677	0.050	0.108	0.146	-2.108
		(1.063)	(1.435)	(0.050)	(0.485)	(0.174)	(0.239)	(0.093)	(1.268)
58	38195	9.861	10.212	19.251	2.518	0.168	0.341	0.257	-1.545
		(1.417)	(1.057)	(0.050)	(0.572)	(0.314)	(0.359)	(0.145)	(0.930)
59	38199	8.447	8.418	19.218	2.251		0.134	0.100	-2.355
		(0.764)	(0.988)	(0.050)	(0.575)		(0.253)	(0.062)	(1.185)
60	38245	8.762	9.029	19.847	2.942		0.151	0.199	-2.595
		(0.870)	(0.867)	(0.138)	(0.579)		(0.265)	(0.107)	(0.839)
SCIENCE-BASED INDUSTRIES									
61	35222	9.432	9.394	19.231	2.853	0.162	0.653	0.359	-2.148
		(1.174)	(1.309)	(0.111)	(0.557)	(0.300)	(0.384)	(0.199)	(0.842)
62	35605	8.506	8.801	16.529	2.348		0.301	0.140	-2.819
		(0.613)	(0.833)	(0.017)	(0.569)		(0.413)	(0.074)	(0.813)
63	35606	8.403	8.579	16.529	2.496	0.002	0.465	0.131	-2.594
		(0.884)	(1.339)	(0.017)	(0.586)	(0.019)	(0.458)	(0.099)	(0.949)
64	35609	8.454	8.439	16.529	2.261	0.010	0.218	0.137	-2.770
		(0.768)	(0.986)	(0.017)	(0.453)	(0.098)	(0.347)	(0.071)	(0.832)
65	38396	9.986	9.977	18.227	2.466	0.050	0.208	0.217	-1.152
		(1.262)	(1.453)	(0.065)	(0.580)	(0.134)	(0.300)	(0.163)	(0.880)

TABLE A.2 *Industrial Classification*[a]

No.	Industry	ISIC
RESOURCE-INTENSIVE INDUSTRIES		
1	Crude vegetable and animal cooking oil	31151
2	Macaroni, spaghetti, noodle and the like	31171
3	Bakery products	31179
4	Food made of chocolate and sugar confectionery	31192
5	Soya sauce	31241
6	All kinds of chip (shrimp chip, fish chip etc)	31251
7	Cake, pastry and similar products	31272
8	Other food products n.e.c	31279
9	Prepared animal feeds	31281
10	Soft drinks	31340
11	Dried tobacco and processed tobacco	31410
12	Clove cigarettes	31420
13	Other type of cigarettes (cerutu, kelembak menyan)	31440
14	Sawmills	33111
15	Moulding and building components	33112
16	Plywood	33113
17	Laminated board including decorative plywood	33114
18	Plaits made of rattan and bamboo	33131
19	Furniture and fixtures mainly made of wood	33211
20	Herbal medicine	35224
21	Tire and inner tubes	35511
22	Vulcanized tire	35512
23	Crumb rubber	35523
24	Products of rubber n.e.c	35593
25	Household wares made of porcelain	36111
26	Structural materials made of porcelain	36112
27	Structural cement products	36321
LABOUR-INTENSIVE INDUSTRIES		
28	Wearing apparel made of textile (garments)	32210
29	Leather tanneries	32312
30	Footwear for daily use	32411
31	Other manufacturing industries n.e.c	39090
SCALE-INTENSIVE INDUSTRIES		
32	Spinning mills	32111
33	Weaving mills except gunny and other sacks	32114
34	Finished textiles	32115
35	Printed textiles	32116
36	Batik	32117
37	Made up textiles	32121
38	Knitting mills	32130
39	Textile n.e.c	32190
40	Cultural papers	34112
41	Industrial papers	34113
42	Boxes made of paper and cardboard	34120
43	Printing, publishing and allied industries	34200
44	Pesticides	35142
45	Paints, varnishes and lacquers	35210

46	Soap and cleaning preparations, including tooth paste	35231
47	Cosmetics	35232
48	Adhesive	35291
49	Steel rolling industry	37103
50	Motor vehicle bodies	38432
51	Motor vehicle component and apparatus	38433
52	Bicycle and tricycles components	38444
DIFFERENTIATED INDUSTRIES		
53	Kitchen ware made of aluminium	38113
54	Kitchen ware made of metal other than aluminium	38114
55	Furniture and fixtures primarily made of metal	38120
56	Nail, screw and bolts	38191
57	All kind of metal containers	38193
58	Metal pipe and pipe fitting	38195
59	Products of metal n.e.c	38199
60	Other industrial machinery and equipments n.e.c	38245
SCIENCE-BASED INDUSTRIES		
61	Drugs and medicines	35222
62	Furniture and fixtures mainly made of plastics	35605
63	Plastics bags, containers	35606
64	Plastic products n.e.c	35609
65	Electric and telephone cables	38396

[a] Classification of industries into the five categories is based on OECD (1987).

TABLE A.3 *Decomposition of Productivity Growth*[a]

No.	ISIC	Annual growth (%)	Period Growth (%)	Contribution to labour productivity growth			
				Ex_ Assimila-tion	Un_ Assimila-tion	Innovat-ion	Potential
RESOURCE-INTENSIVE INDUSTRIES							
1	31279	2.671	20.260	0.967	13.299	4.341	1.653
2	36112	1.485	10.871	1.690	3.760	2.914	2.507
3	35511	1.392	10.158	11.033	1.675	-2.533	-0.017
4	31272	1.127	8.159	2.626	3.477	1.115	0.942
5	31281	1.112	8.049	1.063	5.233	1.168	0.585
6	35593	0.978	7.049	0.837	2.432	3.328	0.453
7	35224	0.941	6.778	0.878	-1.629	6.881	0.648
8	36111	0.881	6.331	-0.905	2.804	4.607	-0.176
9	31151	0.863	6.202	2.981	2.122	-2.099	3.199
10	31340	0.802	5.748	0.886	1.557	3.295	0.010
11	35512	0.781	5.599	1.947	1.950	1.900	-0.198
12	31241	0.592	4.215	3.314	1.302	-0.396	-0.004
13	35523	0.582	4.144	0.409	1.472	2.018	0.245
14	33114	0.512	3.640	3.346	-0.377	0.449	0.222
15	31420	0.368	2.601	0.983	1.216	-0.096	0.498
16	31192	0.292	2.059	0.585	-1.569	2.493	0.550
17	31440	0.270	1.903	8.039	-1.332	-5.000	0.197
18	33131	0.257	1.816	0.274	-0.356	0.354	1.543
19	33113	0.246	1.732	0.578	1.538	-0.399	0.015
20	31171	0.226	1.592	0.134	0.496	0.821	0.140
21	31179	0.193	1.361	-0.013	0.492	0.832	0.051
22	31251	0.166	1.169	0.218	0.446	0.421	0.084
23	33211	0.102	0.713	0.467	0.361	-0.151	0.036
24	33111	0.085	0.595	0.101	0.444	0.076	-0.025
25	36321	0.083	0.580	0.090	0.391	0.061	0.038
26	31410	0.067	0.469	-0.017	0.428	0.072	-0.014
27	33112	0.040	0.281	-0.083	0.359	0.112	-0.107
LABOUR-INTENSIVE INDUSTRIES							
28	32312	2.794	21.272	6.682	11.266	-0.544	3.868
29	39090	2.166	16.184	3.393	5.333	2.505	4.953
30	32411	1.514	11.093	-4.279	3.131	12.177	0.065
31	32210	0.124	0.870	0.087	0.313	0.411	0.059
SCALE-INTENSIVE INDUSTRIES							
32	37103	2.936	22.450	2.048	17.149	1.529	1.723
33	35231	2.170	16.217	4.403	6.542	1.888	3.383
34	38444	1.691	12.454	5.478	4.519	0.149	2.307
35	34120	1.406	10.271	5.935	-0.524	1.089	3.771
36	38433	1.106	8.000	-1.812	9.459	1.460	-1.108
37	35291	1.063	7.680	-1.408	8.080	0.880	0.128
38	35210	1.060	7.661	2.811	3.364	1.587	-0.101
39	35142	1.031	7.447	1.342	5.307	2.181	-1.383
40	32111	1.003	7.239	3.231	4.658	-0.876	0.225

41	32116	0.934	6.723	-0.074	2.117	4.873	-0.194
42	32115	0.839	6.024	0.305	3.464	1.615	0.639
43	32117	0.674	4.811	1.951	0.628	2.267	-0.035
44	38432	0.540	3.844	3.497	1.023	-1.438	0.761
45	35232	0.489	3.471	-0.868	2.705	0.119	1.515
46	34112	0.316	2.234	-0.777	4.177	-4.352	3.187
47	32130	0.282	1.992	-0.633	-0.216	2.098	0.744
48	32114	0.254	1.789	0.130	0.787	0.698	0.174
49	32121	0.205	1.445	0.136	0.003	1.209	0.098
50	34113	0.121	0.848	-0.509	-0.494	1.539	0.312
51	34200	0.106	0.743	0.021	0.216	0.208	0.298
52	32190	0.065	0.455	-1.100	-0.657	2.201	0.011
DIFFERENTIATED INDUSTRIES							
53	38199	3.048	23.387	-0.355	19.872	2.677	1.194
54	38245	2.071	15.429	-2.448	13.421	2.402	2.055
55	38120	1.218	8.841	1.202	6.532	1.564	-0.458
56	38193	0.838	6.014	3.657	0.307	3.706	-1.656
57	38113	0.749	5.366	2.076	2.268	1.134	-0.113
58	38114	0.433	3.069	2.367	-0.715	1.225	0.192
59	38191	0.248	1.747	-1.148	1.619	0.158	1.119
60	38195	-0.142	-0.992	-1.929	1.895	-1.179	0.221
SCIENCE-BASED INDUSTRIES							
61	38396	6.532	55.723	17.532	23.199	8.096	6.895
62	35609	0.718	5.133	2.344	2.036	0.617	0.137
63	35222	0.393	2.783	0.256	1.157	1.072	0.298
64	35605	0.344	2.434	0.389	1.227	0.476	0.343
65	35606	0.267	1.881	0.287	1.529	0.136	-0.071

[a] Industries are sorted in the descending order of annual labour productivity growth.