Industry Canada Industrie Canada

Working Paper Series / Collection Documents de travail

RESEARCH AND DEVELOPMENT COMPOSITION AND LABOUR PRODUCTIVITY GROWTH IN 16 OECD COUNTRIES

Ram C. Acharya, Industry Canada
Serge Coulombe, University of Ottawa and Industry Canada

Working Paper 2006-02

Canada

Working Paper Series / Collection Documents de travail

RESEARCH AND DEVELOPMENT COMPOSITION AND LABOUR PRODUCTIVITY GROWTH IN 16 OECD COUNTRIES

Ram C. Acharya, Industry Canada
Serge Coulombe, University of Ottawa and Industry Canada

Working Paper 2006-02

IC 60040

Revised May 2006

To obtain copies of documents published under the Working Paper Series, please visit : http://strategis.ic.gc.ca/epic/internet/ineas-aes.nsf/en/h_rao1967e.html or contact:

Publications Coordinator
Micro-Economic Policy and Analysis
Industry Canada
10th Floor, East Tower
235 Queen Street
Ottawa, Ontario K1A 0H5

Tel.: (613) 952-6411; Fax.: (613) 991-1261
E-mail: mepa.apme@ic.gc.ca

Pour obtenir des exemplaires des documents publiés dans la collection des documents de travail, cliquer sur http://strategis.ic.gc.ca/epic/internet/ineas-aes.nsf/fr/h_rao1967f.html ou s'adresser à :

Coordinatrice des publications
Analyse de la politique micro-économique
Industrie Canada
10e étage, tour Est
235, rue Queen
Ottawa (Ontario) K1A 0H5

Tél.: (613) 952-6411; Fax.: (613) 991-1261
Courriel: mepa.apme@ic.gc.ca

Acknowledgements

We would like to thank Renée St-Jacques, Richard Roy, Someshwar Rao, Surendra Gera, Jianmin Tang and Jean McCardle for their comments on an earlier version of the paper.

Abstract

Using data for 16 OECD countries from 1973 to 2000, we show that growth in labor productivity is highly responsive to business research and development (R&D) expenditures. Increasing business R&D intensity by 10 percent increases labor productivity in the long run by 2.4 to 5 percent. R&D expenditures on higher education also have a significant positive effect on labor productivity growth. In our decomposition of the sectoral R&D into a pure R&D intensity effect and a sectoral size effect, results show that elasticity of labor productivity with respect to these variables differs by sector. The positive size effect dominates the high-tech manufacturer, whereas it is the intensity effect that drives the positive correlation between medium-low-tech manufacturer R&D and labor productivity.

Key words: *R&D, labor productivity convergence, spillover, R&D size effect, R&D intensity effect*

Résumé

À l'aide de données concernant 16 pays de l'OCDE, pour la période de 1973 à 2000, nous montrons que la productivité du travail dépend beaucoup des dépenses en recherche-développement (R-D) des entreprises. Une augmentation de 10 p. 100 des activités de R-D menées par les entreprises se traduit par une hausse à long terme de 2,4 à 5 p. 100 de la productivité du travail. Les dépenses en R-D dans le secteur de l'enseignement supérieur ont aussi un effet positif important sur l'accroissement de la productivité du travail. Dans notre décomposition de la R-D sectorielle en un pur effet d'intensité de la R-D et en un effet d'échelle sectoriel, les résultats indiquent que l'élasticité de la productivité du travail relativement à ces variables diffère selon le secteur. L'effet d'échelle positif domine chez les fabricants de produits de haute technologie, tandis que l'effet d'intensité entraîne une corrélation positive entre la R-D effectuée par les fabricants de produits à coefficient moyen et faible de technologie et la productivité du travail.

Mots clés : R-D, convergence de la productivité du travail, retombées, effet d'échelle de la R-D, effet sur l'intensité de la R-D

I. Introduction

One of the important lessons learned from the wave of empirical growth research in the last 15 years is that no single factor determines a country's growth rate. Using a broad set of 88 countries that includes both developed and less-developed countries, Xavier Sala-i-Martin et al. (2004) identify 18 variables (out of a set of 67 potential candidates) that are significantly related to growth. However, most of these significant variables represent differences between the less- and most-developed countries. The list of potential variables to explain economic growth becomes much smaller when one attempts to explain standard-of-living differences across developed countries. From both a theoretical and an empirical point of view, the various measures of R&D expenditures are generally considered the most important of these potential variables. Since R&D is carried out mostly in developed countries and the extent of the R&D varies through time and across countries, its ability to explain the variation in productivity growth in developed countries can be potentially very high. The findings of Rachel Griffith et al. (2004) indicate that R&D stimulates productivity growth through a technological catch-up and an innovation channels in a panel data study of industries and twelve developed countries.

Along this line, the objective of this paper is to evaluate empirically the contribution of various components of R&D expenditure to promoting economic growth across a set of countries in the Organization for Economic Co-operation and Development (OECD). More specifically, we will address the following questions: How effective are private and public R&D expenditures in raising labor productivity in developed countries? As for the performance of public R&D, do government intramural R&D and higher education R&D have similar effects? Does a dollar spent on R&D in every sector of the economy has the same effect or does it differ by sector? Is it the R&D intensity in the sector or the size of the sector or both that matters for overall labor productivity growth? What is the role of foreign R&D in promoting domestic labor productivity? To answer these questions, we use a time-series and cross-section (TSCS) empirical model of annual data from 1973 to 2000 for 16 OECD countries.[1] Due to data limitations, the empirical analysis dealing with public R&D covers only the period of 1981 to 2000, and the decomposition of business R&D into R&D intensity and size of the sectors is analyzed for the 1979 to 2000 period.

The questions posed are not entirely new; previous researchers have attempted to answer some of them. Broadly speaking, two threads of literature deal with cross-country R&D studies. One estimates the impact of R&D expenditure on various measures of labor productivity growth; the second focuses on R&D’s impact on total factor productivity (TFP) growth. Thus the estimated coefficients on the R&D variables in the first type of model capture the total effect

[1] The countries included in the study are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, the United Kingdom, and the United States.

(both direct and spillover) of R&D in the economy. The second thread, studying the relationship between TFP growth and R&D, estimates only the spillover effects of R&D.[2]

The first type of literature, pioneered by Walter Nonneman and Patrick Vanhoudt (1996), uses the now-standard convergence-growth regression framework, derived from the transitional dynamics of the neo-classical growth model (N. Gregory Mankiw et al., 1992).[3] Nonneman and Vanhoudt's (1996) contribution extended Mankiw et al. (1992) by incorporating the R&D capital as an additional explanatory variable into the extended Solow growth model.[4] In this framework, they find that the Solow model, augmented further by the addition of R&D, has substantially greater explanatory power compared with that of Mankiw et al. (1992), and that the R&D variable is significant at the 10 percent level. The positive partial correlation between aggregate R&D expenditure and GDP per capita or labor productivity growth across OECD countries has been confirmed in Katarina Keller and Panu Poutvaara (2003) and OECD (2003).

In the second type of literature, several studies have estimated the impact of R&D (both domestic and foreign) on TFP growth.[5] Dominique Guellec and Bruno van Pottelsberge de la Potterie (2001), in a study closely related to ours, investigate the long-term effect of various types of R&D using an error-correction model (ECM) for 16 OECD countries over the period

---

[2] As explained in Charles R. Hulten (2001), since the calculation of TFP includes total production costs including R&D capital any positive relationship between TFP and R&D capital is considered a spillover effect. This is particularly so in business R&D. In this case, the private resources devoted to R&D are included in the economy's stock of capital and pool of labor at the aggregate level. Thus, if there are no spillovers of R&D and the standard assumptions underlying the calculation of TFP hold (notably, perfect competition and constant returns to scale at the aggregate level), then there should be no relationship between these two variables. The literature showing a positive relationship between these two variables is therefore the proof of the existence of spillover effects of R&D.

[3] In a TSCS framework, a convergence-growth model might be viewed as a special case of an error-correction model (ECM) describing the adjustment of labor productivity toward its long-run equilibrium (steady-state) level. See Serge Coulombe (2005) for a discussion of the relationship between an ECM framework, TSCS models and convergence-growth regressions. The empirical convergence-growth analyses as in Mankiw et al. (1992) and Nonneman and Vanhoudt (1996) are based on pure cross-section data.

[4] Mankiw et al. (1992) is an augmented Solow growth model, where they include physical capital as in Solow and augment it with the inclusion of human capital as another determinant of per worker GDP.

[5] Some of these are Griliches (1979; 1994), Jeffrey I. Bernstein and M. Ishaq Nadiri (1988), David T. Coe and Elhanan Helpman (1995), Wolfgang Keller (2002), and Kul B. Luintel and Mosahid Khan (2005).

1980 to 1998. Our results regarding the relative effect of public and private R&D expenditures differ from theirs to some extent. As we will see later, it also appears that some of their results lack robustness for alternative econometric specifications. Furthermore, in contrast to their reliance on just aggregate-level data, we decompose private R&D expenditure by sector and estimate the sectoral impact of R&D.

Despite the usefulness of the second approach in estimating R&D spillover, we believe that the first approach is preferable for our purpose for the following reasons. First, for cross-country studies, the convergence-growth model focusing on labor productivity or per capita GDP adjustment is based on a sound theoretical framework. Unlike labor productivity convergence, to our knowledge there in no theoretical model predicting that TFP levels should adjust in a similar pattern across countries. Second, considering the data complexity related to measurement errors when computing even one country's TFP, it is very challenging to use cross-country TFP growth. Third — and most important as shown in a seminal work of Robert E. Hall (1988) — if there are nonconstant returns and imperfect competition, TFP will be a biased measure of actual unobserved productivity growth. Following Paul M. Romer (1990), we know that R&D is associated with increasing returns to scale and imperfect competition. If that happens to be the case, then what we consider spillover effects of R&D on TFP would be a biased measure. Hence we follow the first approach and use labor productivity growth, a term closely related with per capita GDP growth, as a dependent variable.[6]

The paper contributes to the existing literature in three ways. First, we estimate the effect of the various components of R&D by decomposing R&D into private and public categories and by dividing public R&D into higher education and government. Given the fact that private and public R&D can complement as well as substitute, it is important to incorporate both types of R&D separately. Furthermore, in the existing Solow augmented models, there is no control for foreign R&D spillover. By introducing foreign R&D as a control, this paper not only sharpen the precision of the estimate of returns to domestic R&D but will also allow us, as a by-product, to measure the impact of foreign R&D on domestic productivity.

Second, we provide a sectoral dimension to these models by estimating separately the impact of business R&D on high-tech manufacturers, medium-high-tech manufacturers, medium-low-tech manufacturers, low-tech manufacturers, and services industries. This extension is particularly noteworthy as there is a general belief that R&D in high-tech sectors should generate a higher return to the economy compared with R&D in other sectors. This paper, as far as we are aware, will be the first to be able to test this perception. We also decompose the impact of sectoral R&D on labor productivity into a pure intensity and sectoral-size effects which allows us to understand the relative importance of R&D intensity increase in a given sector and size increase of a sector with given intensity.

Third, rather than studying the impact of R&D on GDP per capita and TFP, we study the impact of R&D on labor productivity, controlled for investment intensity. We thereby escape the problem related to estimating TFP. Our results should not be biased even if the usual assumptions of constant returns to scale and perfect competition, used in computing TFP growth, do not hold.

The main findings of the paper are as follows. The total effect of business R&D is positive and strongly significant in all econometric specifications. The result shows that a country with business R&D intensity 10 percent higher than the typical OECD country ends up

[6] Note that labor productivity growth is equal to the growth in output per working-age person *plus* the growth in the employment to working-age-population ratio. Since the latter ratio does not change substantially among OECD

on a steady-state growth path with a labor productivity level between 2.4 and 5 percent higher than the typical OECD country. In public R&D, only the higher education component produces a positive effect on labor productivity but its effect is not as great as that of business R&D. The effect of government intramural R&D on labor productivity growth is not significant; this is not surprising given that much intramural governmental R&D is in support of regulatory functions and therefore not expected or meant to have an impact on labor productivity.

The results in sectoral analysis show that the high-and medium-tech sectors' R&D is the main source of labor productivity growth, whereas the R&D activities in low-tech and services sectors are not significantly correlated with labor productivity growth. In the high-tech sector, the positive effect of R&D on productivity is driven only by the size of the sector, not by the R&D intensity in this sector. Neither size changes nor R&D intensity changes in medium-high-tech manufacturer affects labor productivity. Interestingly, the R&D intensity and size of medium-low-tech manufacturer affects labor productivity in opposite directions: the R&D intensity effect is positive whereas the size effect is negative.

The role of foreign R&D spillover in raising domestic labor productivity growth is positive but not robust. This lack of robustness might be attributed to the fact that foreign R&D spillover may not be measured adequately with the trade transmission channel. Furthermore, it appears that foreign R&D is correlated with public R&D and some sectoral business R&D. Overall, once those correlations are taken into account, the impact of foreign R&D becomes prominent in raising domestic labor productivity growth.

The rest of the paper is organized as follows. In Section II, we develop the empirical methodology. The data are described briefly in Section III. In Section IV, we discuss results for the relationship between labor productivity growth and public and private R&D. In this section,

---

countries, growth in output per working age population mimics very closely the growth in labor productivity.

we also describe the results by decomposing the aggregate R&D expenditure into five sectors. We conclude in Section V.

II. Theoretical model and empirical methodology

We investigate the relationship between various R&D indicators and economic growth across 16 OECD countries by using the convergence-growth framework that is now the standard empirical approach for analyzing cross-country aggregate data. This empirical approach, based on the theoretical work of Mankiw et al. (1992) and Robert J. Barro and Xavier Sala-i-Martin (1992), is derived from the convergence property of the neo-classical growth model and describes the dynamic adjustment toward the steady-state. The convergence property states that the growth rate of labor productivity (log difference) measured in efficiency units of labor $\Delta Y_{i,t}$, for country *i* during period *t*, is a function of the gap between its steady-state (log) level value $Y_{i,t}^{*}$ at time *t* and its initial (log) level $Y_{i,t-1}$ as given by $\Delta Y_{i,t} = -\beta\left(Y_{i,t}^{*} - Y_{i,t-1}\right)$.

For a model with yearly data, $-\beta$ is the annual speed of convergence toward the steady-state. The convergence property is usually tested empirically with the growth rate of labor productivity being regressed on its initial level and a set of control variables, $Z_{i,t}$, used as proxies for the steady-state level, $Y_{i,t}^{*}$. Following Serge Coulombe and Frank C. Lee (1995) and Nazrul Islam (1995), the adjustment model of labor productivity is often tested by pooling time-series and cross-section (TSCS) data — cross-section being either cross-country or cross-region. With the TSCS technique, the error term can be modeled in a two-way error-correction model with time dummies and fixed effects:

(1) $$\Delta Y_{i,t} = \beta Y_{i,t-1} + \alpha Z_{i,t} + \phi_i + \theta_t + u_{i,t},$$

where $u_{i,t}$ is the idiosyncratic disturbance that captures the effect of country-specific shocks temporarily affecting the economy *i* during period *t*. The fixed effects ϕ_i capture the unobserved time-invariant heterogeneity across countries, such as the initial level of technology.[7] The use of time dummies θ_t in a TSCS empirical model implies that all variables are transformed using a cross-sectional demeaned procedure. In this case, all common shocks to countries are deleted from the analysis.

The first results reported in this study come from various estimations of the following specific formulation of equation (1):

$$\text{(R1)} \qquad \begin{aligned} \Delta Y_{it} &= \beta Y_{it-1} + \alpha_c CC_{it} + \alpha_I I_{it} + \alpha_n N_{it} + \alpha_o OPEN_{i,t} + \alpha_{br} BR_{it} + \\ &+ \alpha_{pr} PR_{it} + \alpha_{fr} FR_{it} + \gamma_{br} \Delta BR_{it} + \gamma_{pr} \Delta PR_{it} + \gamma_{fr} \Delta FR_{it} + \sigma_g G + \phi_i + \theta_t + u_{it}. \end{aligned}$$

Since we are working with an annual data framework, a measure of cyclical component, $CC_{i,t}$, has been added to control for short-run business cycles. The next three variables used as proxies in $Z_{i,t}$ are the logarithm of the investment to GDP ratio, $I_{i,t}$; the annual growth rate of the population, $N_{i,t}$; and the logarithm of the trade (export *plus* import) to GDP ratio, $OPEN_{i,t}$. Among the control variables, the first two, $I_{i,t}$ and $N_{i,t}$, are the determinants of the steady-state level in the closed economy version of the Solow growth model; and the trade share, $OPEN_{i,t}$, is the usual proxy for openness in the trade and growth literature (Jonathan Temple, 1999).[8] And G is the German 1991 dummy.

---

[7] The drawback of using fixed effects in a TSCS framework of this type is that potential controls, Z_i, which are time invariants or change slowly through time such as a democracy or a rule of law indexes, cannot be used in the regression.

[8] In (non-reported) regressions, we used the log of average years of schooling, a measure of human capital, based on Angel de la Fuente and Rafael Doménech's (2002) schooling data as additional control. The point estimates of the human capital variable were not close to being significant. Furthermore, the introduction of the human capital variable modifies only marginally the point estimate and the *t* statistics of the other variables. These negative results regarding the effect of the schooling indicator on labor productivity across OECD countries concur with the findings

The main contribution of this paper is the consideration of a variety of R&D indicators in the $Z_{i,t}$. In the regression set-up given by (R1), we focus on separating the effects of public and private R&D expenditure to GDP ratios on labor productivity growth. To this end, we use $BR_{i,t}$, the log of business performed R&D expenditure to GDP ratio, and three alternative measures of public R&D to GDP ratios, $PR_{i,t}$, namely, public R&D in higher education, government R&D, and finally the sum of the two.

Furthermore, along the line of an open economy model, we also include an index of foreign R&D expenditure to foreign GDP ratio, $FR_{i,t}$, to control for international R&D spillovers. The Coe and Helpman (1995) study triggered a substantial number of studies which try to explain the relationship between foreign R&D capital stock and domestic TFP growth. In this effort, some researchers use international trade as a transfer mechanism of foreign R&D spillover, as did Coe and Helpman (1995); others use foreign direct investment, while yet others use both (Keller, 2004, provides a detailed survey of foreign technology diffusion). In this paper, we use trade flows as a transmission mechanism of foreign R&D. As shown in Appendix 1, we use the share of imports normalized by foreign country GDP as weight to aggregate the foreign R&D of 16 OECD countries. Finally, in the spirit of an ECM, we have also included the first difference of all R&D variables in the set of controls.[9]

---

of Coulombe et al. (2004). They argue for using literacy test scores rather than average years of schooling, stressing that literacy test scores are more comparable across countries than years of schooling. Unfortunately, the literacy data are not available for the set of 16 OECD countries used in this paper. As a result, human capital is not properly controlled in our model. To the extent that R&D and human capital are complements, the estimated effects of R&D on labor productivity growth may be overestimated.

[9] Before proceeding further, one technical comment might be useful here. Note that the point estimates and t-statistics of *BR*, *PR* and *FR* variables will be the same whether they are used in lagged forms or contemporaneously as long as their first differences are also included in the list of regressors. Consequently, adding the first differences in the list of regressors is useful in that we do not have to test for various lag structures for the level of R&D variables.

In this modeling, the short-run dynamics of R&D spending are captured by the $\hat{\gamma}$ parameters, and the long-run level effects of the various R&D measures and the other steady-state determinants on the level of labor productivity are captured by $-\hat{\alpha}/\hat{\beta}$. It is important to note at this point that, as in any other dynamic regression set-up of this type, as long as $-1 < \beta < 0$, the model converges to a steady-state regime where the growth rate of labor productivity in all countries is equal to the common growth rate of technological progress.[10]

The second empirical model used in this paper is a variant of (R1) and is designed to differentiate the effect of various sectoral business R&D expenditures to GDP ratio, $BR_{i,t}^{j}$:

(R2)
$$\Delta Y_{it} = \beta Y_{it-1} + \alpha_c CC_{it} + \alpha_I I_{it} + \alpha_n N_{it} + \alpha_o OPEN_{i,t} + \sum_{j=1}^{5} \alpha_{br}^{j} BR_{i,t}^{j}$$
$$+ \alpha_{fr} FR_{it} + \sum_{j=1}^{5} \gamma_{br}^{j} \Delta BR_{i,t}^{j} + \gamma_{fr} \Delta FR_{it} + \sigma_g G + \phi_i + \varphi_t + u_{it},$$

where *j* indexes the five sectors: high-tech manufacturers, medium-high-tech manufacturers, medium-low-tech manufacturers, low-tech manufacturers, and services. In this set-up, the public R&D variables are withdrawn from the control list, allowing us to expand the study period, from 1973 to 2000. The estimation of the above equation allows us to understand which sectors are more important in labor productivity growth. However, since the control variable is the sectoral R&D to aggregate GDP, it does not tell us whether the sectoral effect is driven by sectoral R&D intensity or the size of the sector. To understand this decomposition, we estimate a slightly different equation given in (R3):

---

[10] But this does not mean that the long-run level of labor productivity will be the same across countries: each country will converge to its own steady-state level. The relative long-run levels of labor productivity across countries could be different as they are determined by their respective $Z_{i,t}$. Convergence implies that, starting from an initial steady-state situation, a shock to one of these control variables exerts a temporary effect on the growth rate of labor productivity during the transition to the new steady-state, and a long-run effect on the relative level of labor productivity.

$$\text{(R3)} \quad \begin{aligned} \Delta Y_{it} &= \beta Y_{it-1} + \alpha_c CC_{it} + \alpha_I I_{it} + \alpha_n N_{it} + \alpha_o OPEN_{i,t} + \sum_{j=1}^{5} \alpha_{ri}^{j} RI_{i,t}^{j} + \sum_{j=1}^{5} \alpha_s^{j} S_{i,t}^{j} \\ &+ \alpha_{fr} FR_{it} + \sum_{j=1}^{5} \alpha_{ri}^{j} \Delta RI_{i,t}^{j} + \sum_{j=1}^{5} \alpha_s^{j} \Delta S_{i,t}^{j} + \gamma_{fr} \Delta FR_{it-1} + \sigma_g G + \phi_i + \varphi_t + u_{it}, \end{aligned}$$

The only difference between (R2) and (R3) is that in the latter, the variable BR — the log of industry level business R&D to GDP ratio — is decomposed into log of industry business R&D to industry value added ratio (*RI*) and the log of industry value added to total GDP ratio (*S*). More, specifically, $BR_{i,t}^{j} = \ln\left(r_{i,t}^{j} / Y_{t}^{j}\right) \equiv \ln\left(r_{i,t}^{j} / y_{i,t}^{j} \bullet y_{i,t}^{j} / Y_{t}^{j}\right) \equiv RI_{i,t}^{j} \bullet S_{i,t}^{j}$, where r_i denotes business R&D in sector i, y_i denotes value added in sector *i*, and *Y* is total GDP. In this specification, RI measures the partial effect of R&D intensity, for a given size in terms of value added for the sector, and (*S*) captures a pure sectoral-size effect, for a given sectoral R&D intensity.

Regression models (R1) and (R2) are estimated using various TSCS techniques. To tackle the heteroscedasticity problem — an important issue in TSCS analysis — we present results from iterated feasible generalized least-square (FGLS) estimations with cross-sectional weights. With this technique, we also report consistent standard errors (HCCME) that are robust to the remaining time-series heteroscedasticity. We also report results from seemingly unrelated regression (SUR) estimations. SUR, which is a Parks estimator, is the least restricted TSCS estimation technique as the residuals are assumed to be both cross-sectional heteroscedastic and contemporaneously correlated. Parks estimations, however, are also known to potentially produce standard errors that lead to extreme confidence, particularly when the number of time series is not much larger than the number of cross-sections (Nathaniel Beck and Jonathan N. Katz 1995). For example, in all regression specifications dealing with model (R1) for which the sample period was restricted to 1981–2000 due do data availability on public R&D, SUR estimations generated high t-statistics for most point estimates compared to FGLS.

We also report results of (R1) and (R2) using system estimation with instrumental variables (IV). First, in all IV estimations, the log level of labor productivity, lagged by two years ($Y_{i,t-2}$), has been included in the list of instruments. This procedure is known to decrease the propensity to overestimate the convergence speed due to measurement error in this type of model (Barro and Sala-i-Martin, 2004) and to reduce Stephen Nickell's (1981) bias associated with fixed-effect estimations of dynamic TSCS models. We also use IV techniques to surmount the problems of endogenous explanatory variables. To this end, we have included one-year lag of population growth, investment to GDP ratio, and openness variables in the list of instruments. We report the results of two different system estimations with IV. The first set of results comes from iterated weighted two-stage least-squares (2SLS) estimation, which is the IV system equivalent to FGLS estimations. The second set is from three-stage least-squares (3SLS) estimation, which is the IV estimator analogue to SUR. It thus has the same problem as SUR regarding overconfidence since it is also a Parks estimator.

III. Data

Most of the data used in this study come from the OECD (a more detailed account of the data is given in Appendix 1). The aggregate R&D data are from the Main Science and Technology Indicators database of the OECD. The data series we used are in 2000 constant prices and in purchasing power parities (PPPs). The industry level R&D data are from the Analytical Business Enterprise R&D (ANBERD) database of the OECD. These current-price PPP data for each country have been converted to constant-price PPPs by dividing them by their own country's GDP deflator (calculated as a ratio of current and constant-price GDP for each country from the OECD database).

All industry-level data have been computed from the International Standard Industrial Classification, Revision 3 (ISIC Rev. 3) and Revision 2 codes. Revision 3 has more industry disaggregation compared with the earlier version (Revision 2). Since the industry codes in Revision 2 and Revision 3 differ, we use a concordance developed by OECD to convert the Revision 2 into Revision 3 data. Finally, the manufacturing industry data are aggregated into four types of manufacturers (high-tech, medium-high-tech, medium-low-tech and low-tech) using the technology classification (given in Appendix 2) adopted by OECD. We also study aggregate services as a separate sector.

The labor productivity, population growth and investment intensity (investment to GDP ratio) data are taken from Penn World Table (Alan Heston et al., 2002). For labor productivity, we use the series “Real GDP chain per worker at 1996 prices.” Our measure of the business cycle correction, GDP gap in percentage, is obtained from quarterly real GDP data using Hodrick and Prescott’s filter with a smoothing parameter of 1600. The raw data are GDP volume at 2000 constant PPP from OECD (Economic Outlook Quarterly database) for 32 years (1963 to 2004). The quarterly cyclical component was then annualized to fit into our sample framework.

The data on international imports are from the Bilateral Trade database of OECD. For each country, we used import data to calculate the import shares of all individual countries in the sample. These shares were then used as weights to aggregate foreign business R&D expenditure (as shown in Appendix 1). Since import data are available only from 1980, for the years 1973 to 1979, we use the average import shares of 1981 to 1985 as weights. The import shares are computed using data in current-price U.S. dollars.

IV. Results

Results for the regression set-up (R1) are reported in Tables 1 to 3 for three alternative measures of public R&D where the sample runs from 1981 to 2000. Equation (R1) was also estimated by dropping the variables on public R&D and extending the sample period from 1973 to 2000 and the results are reported in Table 4. Results in Table 5 come from the (R2) regression set-up in which the sample period is as in Table 4 and public R&D variable is also taken out, however, the business R&D variable has been divided into five sectors. Finally, results for the regression set-up (R3), in which the sample is limited from 1979 to 2000 and sectoral R&D share in aggregate GDP is decomposed into sectoral R&D intensity and size, are reported in Table 6. In the first subsection below, we discuss the results of Tables 1 to 4 followed by the results of Tables 5 and 6 in the next subsection.

IV.A. Regressions with private and public R&D

Table 1 refers to the (total) public expenditure in R&D (PERD), which is the sum of the government expenditure in R&D (GOVERD) and higher education expenditure in R&D (HERD). Results in Table 2 (Table 3) refer to the regressions for which HERD (GOVERD) is used as the measure of public R&D.

The results for the four non-R&D variables (lagged labor productivity, the business cycle, investment and openness) are consistent and robust in all three tables and four specifications/estimation techniques (FGLS, 2SLS, SUR, 3SLS). Furthermore, their point estimates have the expected sign: a negative fraction for lagged productivity level, indicating conditional convergence; positive for the business cycle, investment intensity and openness variables. The various point estimates for the lagged productivity variable imply that the estimated convergence speed varies between 6.7 and 11.7 percent. This implies that the economy moves halfway to steady-state in about 6 to 12 years.[11]

More importantly, the positive effect of the domestic business expenditure in R&D (BERD) variable is ultra robust in this study. In the 12 reported regression results dealing with private and public R&D variables (all specifications in Tables 1 to 3), the point estimates of the BERD variable are positive and significant at the 1 percent level. On quantitative grounds, the long-term elasticities of these point estimates for this variable vary between 0.24 and 0.50. Thus, according to these results, a country with a business R&D intensity 10 percent higher than the typical OECD country has, in the long run, a labor productivity level between 2.4 and 5 percent higher. This findings imply that, on average, if a country increases its business R&D intensity (percent of R&D in GDP) by 0.1 percent, it will increase its per capita income by 0.9 to 1.8 percent. It works as follows: with given average R&D intensity of 1.6 percent in sample countries, a 10 percent increase in R&D intensity results in an increase of R&D by 0.16 percent of GDP. Thus, an increase of R&D by 0.1 percent of GDP increases labor productivity by 1.5 (= 2.4/0.16 * 0.1) to 3 percent. Considering average employment to population ratio of 0.6, the effect will be an increase in per capita income of approximately 0.9 to 1.8 percent.

This range of elasticities falls within the range of some earlier estimates. For example, summarizing several studies, Nadiri (1993) notes that the elasticities of output with respect to business R&D is in the range of 8 to 30 percent. The OECD (2003) study estimates the elasticity of real output per working-age population to business R&D to be 0.72, which is much higher than our results. Our estimates of long-run labor productivity growth with respect to business

---

[11] This speed of convergence seems rather fast compared with cross-country studies based on pure cross-section information, studies such as Barro and Sala-i-Martin (2004). However, our estimates of the convergence speed concur with many time-series cross-country studies that have used fixed effects. For example, Islam (1995) reports a convergence speed of 9 percent in the fixed-effect specification. The point estimates of population growth also have

R&D intensity are also in line with the elasticities obtained in augmented Solow-type models. For example, in Nonneman and Vanhoudt (1996), the implied estimated elasticity of real GDP per working-age population with respect to R&D intensity is 0.23.[12]

It is not a straightforward matter to compare the R&D elasticities found in this paper with those estimated using TFP growth (rather than labor productivity growth) as the dependant variable. In a simple Cobb-Douglas production function with constant returns to scale, we can show that the average labor productivity growth will be higher than TFP growth if the capital deepening is increasing and the share of labor force with higher marginal product is also increasing.[13] Since we expect this to be the case for our sample of OECD countries, we expect the average labor productivity growth to be higher than TFP growth. However, in such a simple model, if we could control properly for the effects of capital deepening and labor quality in the estimation, then the regression coefficients in (R1) through (R3) can be interpreted as an effect on TFP growth, despite the use of labor productivity growth on the left-hand side.

However, the real world is certainly different from the simple textbook-type model that we have described: the relationship between labor productivity and TFP growth is far from linear. Furthermore, the crucial assumption of constant returns to scale needed for this expression may not hold, further complicating the relationship between labor productivity and TFP growth.

---

the negative sign, as expected from neo-classical growth models. This result, however, is not very robust since it is not significant at the 10 percent level with FGLS and 2SLS in Table 3.

[12] This number is computed from Table IV, upper window, last column, of Nonneman and Vanhoudt (1996) who do not report long-run elasticities.

[13] Let the production function be given by Cobb-Douglas specification such that $Y = AK^{\alpha}L^{\beta}$, where Y is output; K is physical capital; and L is number of workers. With the assumption of constant returns to scale, we can convert this function into labor productivity per hour by dividing both sides of the equation by hours of works, H. Then taking log difference, the per hour output growth function can be written as $\Delta \ln\left(Y/H\right) = \alpha\Delta \ln\left(K/H\right) + \beta\Delta \ln\left(L-H\right) + \Delta \ln\left(A/H\right)$. This shows that the per hour labor productivity growth depends on three factors. The first term on the right-hand side is *capital deepening*, the capital services per hour. The second term is the improvement in *labor quality*, defined as the difference between growth rates of labor input and hour worked. If the hours of work by workers with higher marginal product rises, it raises the overall labor

In this case, even a proper control of capital deepening and labor quality may not make TFP growth equivalent to labor productivity growth. Besides, because of data limitation, we cannot control all other factors that potentially affect labor productivity growth.

Hence the results derived using TFP and labor productivity growth are not directly comparable. More important, in the models that use TFP as a dependent variable — as the direct impact of business R&D on output is already at least partly accounted for in TFP — the elasticities must capture mainly spillovers and possibly extra returns (coming in addition to normal remuneration of capital and labor) arising from R&D. However, elasticities in our model more likely capture the total effect (both direct and spillover) of R&D. Thus it is quite reasonable that our elasticities are higher than those estimated in models with TFP growth as a dependent variable. The OECD study by Guellec and van Pottelsberge de la Potterie (2001) finds the long-term elasticity of TFP growth to be 0.13 with respect to business R&D. Using this number as a norm for spillovers, our long-term elasticities' range of 0.24 to 0.50 means that the direct effect of R&D is in the range of 0.11 (slightly smaller than spillover effect) to 0.27 (more than double spillover effect).

For R&D carried out by the public sector, there is evidence of a positive effect on labor productivity only in the case of HERD. The effect is significant at the 5 percent level in three estimation techniques and is significant at the 10 percent level only in 3SLS.[14] The long-run quantitative effect of HERD is not estimated with great accuracy since it is about four times

---

productivity. The last term is *TFP growth,* which increases labor productivity on a point-for-point basis (see Dale W. Jorgenson and Kevin J. Stiroh [2001] for similar expression).

[14] As for the R&D carried out in the public sector, it is important to note at the start that the HERD variable is highly positively correlated with BERD. In a TSCS framework, this is best illustrated by the results of a simple pooled least-squares bivariate regression where BERD is regressed on HERD (without a constant since both variables are expressed as a deviation from the cross-sectional sample mean). In this test, the slope parameter of the higher education variable was 1.03 with a t-statistic of 18.8 and R^2 of 0.50. The correlation between GOVERD and BERD

smaller (0.06 versus 0.24) when it is estimated with SUR and 3SLS compared with FGLS and 2SLS. Nevertheless, the long-term elasticity of government- and university-performed research on TFP of around 0.17 estimated by Guellec and van Pottelsberge de la Potterie (2001) falls within our wide range of estimates. The point estimates and the standard errors of the higher education variable change only marginally when the business R&D variable is dropped from the regression. This point is worthy of attention since as mentioned earlier, higher education and business R&D are highly correlated.

The hypotheses that the PERD (Table 1) and GOVERD (Table 3) have a positive effect on labor productivity are rejected by the results. Tables 1 and 3 show that the point estimates for these two public R&D variables are even negative and significant at the 1 percent level with the SUR and 3SLS estimations. These results concur with the recent OECD study (2003) that reports a negative and significant estimate for the coefficient of public R&D in per capita output growth regression with the same type of estimation techniques (Table 2.6, Column 2). However, with FGLS and 2SLS specifications, the point estimates for PERD and GOVERD — although insignificant — are positive. In our view, we should not give much weight to SUR and 3SLS results when they conflict with those in FGLS and 2SLS. Parks estimations that correct for the contemporaneously correlated errors in TSCS models (such as SUR and 3SLS) are known, as discussed earlier, to sometimes underestimate the standard errors dramatically and lead to overconfidence. Accordingly, we believe that it is more appropriate to conclude that the public R&D variables, other than university education, have no significant impact on productivity rather than to put the emphasis on the nonrobust negative effect of public R&D.[15]

---

was much weaker. In the same type of bivariate regression (with BERD regressed on GOVERD), the point estimate of the slope parameter was 0.11; the t-statistic was 2.23, and R^2 was close to zero.

[15] We also estimated (R1) using GOVERD and HERD as two separate variables (instead of using the sum, PERD, as done in Table 1). In this specification only HERD was positively significant.

Our results regarding the effect of public R&D, however, are in contrast to those of Guellec and van Pottelsberge de la Potterie (2001) where they report a positive and significant effect for public R&D on TFP growth using SUR and 3SLS estimates. While duplicating their empirical studies using their data bank, we found that their reported results regarding public R&D were not robust with FGLS and 2SLS. Therefore, the significance of their estimates regarding public R&D might well be attributed to the tendency of Parks estimators to provide overconfident results.

Finally, the point estimate of the foreign R&D indicator is positive throughout all specifications in Tables 1 to 3. It is significant, however, only with SUR and 3SLS estimations in Tables 1 and 2 only. The elasticity of labor productivity with respect to foreign R&D varies significantly across various estimations; whenever the foreign R&D variable is significant, its elasticity is in the range of 0.32 to 0.54. This is in line with Guellec and van Pottelsberge de la Potterie (2001) who estimate the long-term elasticity of TFP growth with respect to foreign R&D to be in the range of 0.45 to 0.50.[16] In their models, unlike ours, the foreign R&D variable is significant in all specifications. Again, in duplicating their results, we found that the significance of their variable did not survive to FGLS and 2SLS estimations.

Nevertheless, the insignificance of foreign R&D variable in 8 of the 12 cases and in all of our preferred estimation techniques of FGLS and 2SLS is unexpected. Having said that, we would like to stress that the insignificance of the foreign R&D variable may not necessarily mean that there are no spillover benefits from foreign R&D capital. What it means is that the spillovers of foreign R&D may not be completely transmitted through imports, which is not new

[16] Since the foreign R&D is not accounted for in GDP, even if we have labor productivity on the left-hand side, we will be estimating spillover as if we are using TFP as dependent variable. This is because the domestic opportunity cost of foreign R&D is zero.

in the literature.[17] It may also be due to the fact that, although foreign R&D has spillovers that pass through imports to domestic economy, the test fails to show this result as the foreign R&D variable is correlated with other control variables used in the model. (This issue will be discussed more in the following subsection.)

By dropping the public R&D variable from the list of controls, we are able to extend the sample to the 1973 to 2000 period. The results from this extended sample, displayed in Table 4, illustrate the robustness of the impact of business R&D. The point estimate of business R&D is always positive and significant at the 1 percent level. Furthermore, the long-term elasticities of labor productivity to business R&D falls between 0.28 and 0.53, a range very similar to the one estimated with the shorter sample. The point estimates of the foreign R&D indicator are positive, but the effect is not that robust as the point estimates are not significant at the 5 percent level in three out of four cases.

As for the non-R&D variables, three variables (lagged labor productivity, the business cycles and the openness) display the same robustness as in Tables 1 through 3. They all have the expected sign and are significant at the 1 percent level with all four specifications. However, the effect of the remaining non-R&D variable, investment to GDP ratio, is significant at the 1 percent level only with FGLS and SUR. In IV regression, it is significant only at the 10 percent level with 2SLS estimations, and the t-ratio is only 0.21 with 3SLS. These results illustrate a well-known fact in growth empirics: the correlation between investment and growth does not

[17] In their study, Coe and Helpman (1995) find a positive and qualitatively large effect from import-weighted foreign R&D, where 1 percent increase in R&D capital stock in the United States raises the average productivity of 22 OECD countries by about 0.12 percent. However, Keller (1998) shows that, to generate Coe and Helpman's result, using import share to aggregate foreign R&D variable (implying that import is the spillover channel) as was done in Coe and Helpman (1995) is not essential. Specifically, Keller uses randomly created shares in place of actual bilateral import shares to create the counterfactual foreign knowledge stock. Using this alternative foreign R&D variable yields similarly high coefficients. Given that import shares are not essential to obtain Coe and Helpman's (1995) results, their analysis does not allow us to draw strong conclusions regarding the importance of

always “survive the use of instrumental variables” (Temple 1999, p. 137). Given the potential endogeneity problem, when investment ratio is correlated with the error term, the results of IV estimations should be preferred. The nonsignificant or weakly significant effect of this variable with the IV method somehow tempers the robustness of a positive effect of investment intensity in labor productivity growth.

IV.B. Decomposing the effect of business R&D

We now turn to the sectoral analysis with results presented in Table 5 using the same sample period of 1973 to 2000 as in Table 4 and decomposing the business R&D variable into five sectors: high-tech-manufacturers (HTM), medium-high-tech-manufacturers (MHTM), medium-low-tech-manufacturers (MLTM), low-tech-manufacturers (LTM) and services. The decomposition appears very useful since it yields three different sets of results for technologically different sectors.

First, for the business R&D in high-tech and medium-low-tech, the point estimates are all positive and significant at the 1 percent level. Furthermore, the long-term elasticities appear to be estimated relatively precisely across the various estimation techniques since they vary between 0.13 and 0.16 for the high-tech manufacturing and between 0.10 and 0.19 for the medium-low-tech.

Second, the point estimates of the medium-high-tech manufacturers are all positive, but the result is not robust. The point estimates are not significant at the 5 percent level with FGLS and 2SLS but the *p* values in this case are in the neighborhood of 10 percent. The estimated long-term elasticities for this sector’s business R&D are, however, in the same range as those for the

imports as a vehicle for diffusion. Similarly, Griffith et al. (2005) also find only a small effect of trade in TFP growth (statistically significant only at the 10% level).

high-tech and the medium-low-tech sectors. In this sector too, overall there is some evidence (but not that robust) in favor of a positive effect of this R&D component on labor productivity.

Third, the null hypothesis of a positive and significant effect for the last two components, low-tech manufacturers and services, is clearly rejected by the data. Again, the negative sign is significant even at 1 percent for the low-tech sector with SUR and 3SLS. But we believe that giving too much importance to these results is misleading, given the tendency of Parks estimations to create overconfidence in rejecting the null.

Hence, the robust positive impact of aggregate business R&D on labor productivity in Table 4 should have been driven mainly by business R&D in high-tech and medium-low-tech manufacturers, and less so (if any) by medium-high-tech manufacturers. It seems somewhat counterintuitive that business R&D in medium-low-tech manufacturers is more effective for labor productivity than medium-high-tech manufacturers. However, it should be borne in mind that this result may not necessarily mean that the rate of return to R&D in medium-low-tech manufacturing is higher than in medium-high-tech.

Finally, the point estimates of foreign R&D have improved in the longer time period model compared with those in the shorter period (results in Tables 4 to 5 versus results in Tables 1 to 3). Loosely speaking, they improved after we excluded the public R&D from the estimation. It improves further once we decompose the R&D into five sectors; the coefficients of foreign R&D are now positive and significant at least at the 5 percent level in all four regressions.

Next, we would like to see whether the results in Table 5 are driven by the R&D intensities or by the pure size (industrial structure) effects. For this purpose, we estimate the specification (R3) by limiting the sample from 1979 to 2000, as sectoral value added data prior to 1979 were not consistently available across countries. As the variables population growth rates, German dummy and the R&D in LTM sector were not significant, we dropped them from the control and reported only the results on long-run elasticities in Table 6.

The results show that the size effect in the HTM sector increases labor productivity. A country with a HTM sector 10 percent larger than the typical OECD countries ends up on a steady-state growth path with a labor productivity level of 2.6 to 3.4 percent higher. The impact of R&D intensity in the HTM sector is not robust; it is positively significant with FGLS but insignificant with SUR. The relative effectiveness of the size variable in the high-tech sector can result from the fact that the R&D intensity (per unit of value added) is already very high in this sector compared with others. Hence, most potentially successful R&D opportunities in this highly innovative sector has previously been exploited in which case increasing the rate of R&D activity will not be that profitable. However, increasing the number of firms or increasing firms' size opens avenues for new productive R&D activities.

Interestingly, we get the reverse result in the case of the MLTM. In this sector, the overall positive and significant effect of R&D spending (Table 5) is more than driven by the pure size effect as the partial effect of sectoral intensity is negative (Table 6). These results suggest that, in this less innovative sector, some potentially productive R&D activities are not fully exploited. Increasing the size of the sector, leaving the R&D sectoral intensity constant, exerts a negative impact on productivity growth. By contrast, increasing R&D activity stimulates growth on impact and increases the productivity level in the long run. The decomposition of the total effect into a size and a sectoral intensity does not add more insight to the case of MHTM, as the point estimates are not significant. This result concurs with findings for the overall effect of this sector in the shorter sample.[18]

Finally, for the services sector, both increase in R&D intensity and size lower labor productivity growth. The resulting negative size effect might be interpreted as evidence in favor of a Baumol's disease (William Baumol, 1967). However, note that in the longer sample in Table 4, services sector's R&D intensity with respect to overall GDP has no significant impact on labor productivity. The contradictory results in Table 6 with shorter sample, does not allow drawing any conclusions regarding the impact of R&D activities in the services sector.

V. Conclusion

The main lesson from studies focusing on the determinant of growth in a broad set of countries is that rich countries, unlike poor countries, have most of the fundamental determinants right. But disparities in growth performance among rich countries are also observed. The obvious question is: What can we learn from cross-country studies to help orient policy so rich countries, eager to close the gap with the leaders, can do so? Our empirical investigation is an attempt to answer this important question. On theoretical grounds, R&D is considered a good candidate to accelerate growth as it could bring technological progress and also increase the absorptive capacity of the domestic economy to capture spillovers from foreign R&D.

The contribution of our paper is that on empirical grounds, most R&D components, but not all, are positively and significantly correlated to labor productivity growth. The first point of interest arising from this study is that the growth effect of business R&D, unlike public R&D, is positive and strongly significant in all specifications. Results indicate that a country with a business R&D intensity 10 percent higher than the typical OECD country ends up on a steady-

[18] See note to Table 5.

state growth path with a labor productivity between 2.4 and 5 percent higher. This estimated elasticity in the range of 0.24 to 0.50 is substantially larger than the 0.02 share of business R&D in the GDP, an indication of a strong spillover effect of business R&D. On the other hand, among public R&D, only expenditure in higher education affects labor productivity positively and significantly. Furthermore, higher education is highly and positively correlated with business R&D.

A key point of interest in our study is that business R&D in different sectors does not enhance growth in the same way in every sector. We found that high- and medium-tech sectors' R&D are the main source of labor productivity growth. However, in the medium-tech sector, it is mainly the medium-low-tech area rather than the medium-high-tech that generates the stronger effect on labor productivity. Finally, in the low-tech manufacturing and service sectors, R&D activities are not significantly correlated with growth.

This indicates that the return on R&D activities might differ across sectors because the direct return differs, the spillover effects differ, or both. It is entirely possible that the knowledge generated through R&D activities is more non-rival (and be useful for many other sectors of the economy) in the high-tech sector than in the service sector and low-tech manufacturing.

It is also possible that the high- and medium-tech manufactures are disproportionately used more as inputs into other industries than the low-tech manufacturers and services. If this is the case, R&D and the corresponding technological improvements in the high- and medium-tech sectors reduce costs at a faster rate (thereby increasing productivity) than those in low-tech and services. Whatever the reasoning for the varied impact of R&D in the different sectors (some sectors have negative effects on aggregate labor productivity growth), this paper is able to measure more precisely the positive impact of R&D by estimating R&D's impact by sector.

Further decomposition of the effects of R&D on size and intensity effects shows that the only sector that contributes positively in labor productivity growth with increase in its size is high-tech manufacturing (keeping R&D sectoral intensity constant). Increase in the sizes of other sectors either hurts or does not affect labor productivity growth. This result suggests that the industrial structure, particularly with respect with the relative size of the high tech sector, matters for productivity growth. Whereas the intensity effect is not that robust in the high tech sector, a rise in the R&D intensity in the medium-low-tech-manufacturer appears to stimulate productivity growth. Hence, OECD countries with relatively larger high-tech-manufacturer and relatively R&D intensive medium-low-tech manufacturer will have better productivity performance in the long run.

Finally, along with many earlier recent studies, openness to trade appears to be positively and robustly correlated with growth. However, trade channels alone may not be able to fully capture foreign R&D spillover. Hence, to maximize the benefit of foreign R&D spillovers (besides free trade in goods and services), government might encourage other possible channels of foreign R&D spillovers such as the free flow of capital and skilled manpower.

References

Beck, Nathaniel and Katz, Jonathan N. "What To Do (and Not To Do) with Time-Series Cross-Section Data." *American Political Science Review,* September 1995, 89(3), pp. 634-47.

Barro, Robert J. and Sala-i-Martin, Xavier. *Economic Growth.* New York: McGraw-Hill, 2004.

Baumol, William. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crises." *American Economic Review*, 57, June 1967, pp.415-26.

______. "Convergence." *Journal of Political Economy*, April 1992, 100(2), pp. 223-51.

Bernstein, Jeffrey I. and Nadiri, M. Ishaq. "Interindustry R&D Spillovers, Rates of Return, and Production in High-Tech Industries." *American Economic Review Papers and Proceedings*, May 1988, 78(2), pp. 429-34.

Coe, David T. and Helpman, Elhanan. "International R&D Spillovers." *European Economic Review*, May 1995, 39(5), pp. 859-87.

Coulombe, Serge. "Globalization and Regional Disparity: A Canadian Case Study." Unpublished Paper, 2005.

Coulombe, Serge and Lee, Frank C. "Convergence across Canadian Provinces, 1961 to 1991." *Canadian Journal of Economics*, November 1995, 28(4a), pp. 886-98.

Coulombe, Serge; Tremblay, J.-F. and Marchand, S.. *Literacy Scores, Human Capital and Growth across Fourteen OECD Countries.* Ottawa: Statistics Canada, 2004. Cat. No. 89-552-MIE2004011.

De la Fuente, Angel and Doménech, Rafael. "Human Capital in Growth Regressions: How Much Difference Does Data Quality Make? An Update and Further Results." Unpublished Paper, 2002.

Griffith, Rachel; Redding, Stephen and Reenen, John Van. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics*, November 2004, LXXXVI (4), pp. 883-895.

Griliches, Zvi. "The Search for R&D Spillovers." *Scandinavian Journal of Economics*, 1992, 94, pp. S29-47.

______. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics*, Spring 1979, 10(1), pp. 92-116.

Guellec, Dominique and van Pottelsberghe de la Potterie, Bruno. "The Impact of Public R&D Expenditure on Business R&D." *Economics of Innovation and New Technology*, June 2003, 12(3), pp. 225-43.

______. "R&D and Productivity Growth: Panel Data Analysis of 16 OECD Countries" *Oxford Bulletin of Economics and Statistics*, OECD Economic Studies, 2001, pp. 103-25.

Hall, Robert E. "The Relation between Price and Marginal Cost in U.S. Industry." *Journal of Political Economy*, October 1988, 96(5), pp. 921-47.

Heston, Alan; Summers, Robert and Aten, Bettina. Penn World Table Version 6.1 [online]. Center for International Comparisons, University of Pennsylvania (CICUP), October 2002. Available from: http://pwt.econ.upenn.edu/php_site/pwt61_form.php

Hulten, Charles R. "Total Factor Productivity: A Short Biography," in Charles R. Hulten, Edwin R. Dean and Michael J. Harper, eds., *New Developments in Productivity Analysis*, Vol. 62 in NBER Studies in Income and Wealth. Chicago: University of Chicago Press, 2001, pp. 1-47.

Islam, **Nazrul**. "Growth Empirics: A Panel Data Approach." *Quarterly Journal of Economics,* November 1995, 110(4), pp. 1127-71.

Jorgenson, Dale W. and Stiroh, Kevin J. "Raising the Speed Limit: U.S. Economic Growth in the Information Age," in Dale W. Jorgenson and Frank C. Lee, eds., *Industry Level Productivity and International Competitiveness between Canada and the United States.* Ottawa: Industry Canada, March 2001, pp. 5-75.

Keller, Katarina and Poutvaara, Panu. "Do the Augmented Solow Models Rule? A Contribution to the Empirics of Human Capital, R&D, and Economic Growth." Centre for Economic and Business Research, Discussion Paper: DP 2003-13, 2003.

Keller, Wolfgang. "International Technology Diffusion." *Journal of Economic Literature*, September 2004, 42(3), pp. 752-82.

______. "Geographic Localization of International Technology Diffusion." *American Economic Review*, March 2002, 92(1), pp. 120-42.

______. "Are International R&D Spillovers Trade-Related? Analyzing Spillovers among Randomly Matched Trade Patterns." *European Economic Review*, 1998, 42(8), pp. 1469-81.

Luintel, Kul B. and Khan, Mosahid. "Are International R&D Spillovers Costly for the U.S.?" *Review of Economics and Statistics*, November 2004, LXXXVI (4), pp. 896-910.
Mankiw, N. Gregory; Romer, David and Weil, David N. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics*, May 1992, 107(2), pp. 407-37.
Nadiri, M. Ishaq. "Innovations and Technological Spillovers." NBER Working Paper No. 4423, August 1993.
Nickell, Stephen. "Biases in Dynamic Models with Fixed Effects." *Econometrica*, November 1981, 49(6), pp. 1417-26.
Nonneman, Walter and Vanhoudt, Patrick. "A Further Augmentation of the Solow Model and the Empirics of Economic Growth for OECD Countries." *Quarterly Economic Journal of Economics*, August 1996, 111(3), pp. 943-53.
Organization for Economic Co-operation and Development. The Sources of Economic Growth in OECD Countries, Paris, 2003.
______. Innovation Policies: Innovation in the Business Sector, Paris, 2005.
Romer, Paul M. "Endogenous Technological Change." *Journal of Political Economy*, October 1990, 98(5), pp. S71-S102.
Sala-i-Martin, Xavier; Doppelhofer, Gernot and Miller, Ronald I. "Determinants of Long-Term Growth: A Bayesian Averaging of Classical Estimates (BACE) Approach." *American Economic Review*, September 2004, 94(4), pp. 813-35.
Temple, Jonathan. "The New Growth Evidence." *Journal of Economic Literature,* March 1999, 37(1), pp. 112-56.

Table 1. Effects of total public R&D and business R&D on labor productivity growth
Dependent variable is change in log labor productivity
Number of observations = 304 (sample period: 1981-2000)

	FGLS	SUR	2SLS	3SLS
Lagged labor productivity	-0.099	-0.082	-0.080	-0.067
	(-3.57)[a]	(-9.98)[a]	(-3.35)[a]	(-7.24)[a]
Business cycle	0.262	0.113	0.269	0.118
	(3.00)[a]	(15.56)[a]	(3.67)[a]	(13.83)[a]
Investment intensity	0.061	0.047	0.055	0.038
	(4.62)[a]	(11.88)[a]	(3.79)[a]	(7.71)[a]
Population growth	-0.011	-0.009	-0.011	-0.010
	(-1.89)[b]	(-6.05)[a]	(-1.97)[b]	(-5.65)[a]
Openness	0.030	0.030	0.035	0.034
	(2.42)[b]	(6.17)[a]	(3.10)[a]	(6.24)[a]
Germany dummy	-0.040	-0.033	-0.035	-0.031
	(-2.08)[b]	(-9.59)[a]	(-1.97)[c]	(-8.27)[a]
Foreign BERD	0.018	0.026	0.019	0.026
	(0.60)	(2.99)[a]	(0.76)	(2.92)[a]
Domestic BERD	0.029	0.032	0.029	0.029
	(4.00)[a]	(15.63)[a]	(4.43)[a]	(13.25)[a]
Domestic PERD	0.012	-0.018	0.011	-0.016
	(1.13)	(-5.06)[a]	(1.07)	(-4.46)[a]
Long-term elasticities				
Foreign BERD	0.182	0.317[a]	0.238	0.388[a]
Domestic BERD	0.292[a]	0.390[a]	0.363[a]	0.433[a]
Domestic PERD	0.121	-0.220[a]	0.138	-0.239[a]
Adjusted R^2	0.32	0.29		
S.E. of regression	0.02	0.019		

Note: All regressions were estimated in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged and their first difference terms were also included in the estimation. We have not reported the results for first difference terms in the table. T-ratios are in parentheses; t-statistics for FGLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D. PERD is public (government plus higher education) expenditure in R&D.

Long-term elasticities are estimated as follows: for variable *X* (*X* = foreign BERD, domestic BERD and domestic PERD), divide the estimated coefficient for *X* by the opposite of estimated coefficient for lagged labor productivity in the same regression. For example, in the first regression (column 1), the long-term elasticity for foreign BERD is 0.018/0.099 = 0.182.

[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significance at 10 percent level

Table 2. Effects of higher education R&D and business R&D on labor productivity growth
Dependent variable is change in log labor productivity
Number of observations = 304 (sample period: 1981-2000)

	FGLS	SUR	2SLS	3SLS
Lagged labor productivity	-0.083	-0.083	-0.070	-0.072
	(-3.31)[a]	(-11.00)[a]	(-3.25)[a]	(-9.08)[a]
Business cycle	0.303	0.138	0.313	0.138
	(3.54)[a]	(19.75)[a]	(4.31)[a]	(18.38)[a]
Investment intensity	0.064	0.050	0.058	0.045
	(4.84)[a]	(11.72)[a]	(3.93)[a]	(10.23)[a]
Population growth	-0.011	-0.011	-0.012	-0.012
	(-2.11)[b]	(-8.75)[a]	(-2.18)[b]	(-9.60)[a]
Openness	0.033	0.030	0.035	0.033
	(2.59)[a]	(6.46)[a]	(3.07)[a]	(6.35)[a]
Germany dummy	-0.035	-0.038	-0.032	-0.036
	(-1.78)[c]	(-9.99)[a]	(-1.72)[c]	(-8.78)[a]
Foreign BERD	0.022	0.037	0.024	0.039
	(0.75)	(3.26)[a]	(0.93)	(3.19)[a]
Domestic BERD	0.036	0.027	0.035	0.026
	(5.08)[a]	(12.64)[a]	(5.57)[a]	(11.67)[a]
Domestic HERD	0.019	0.005	0.017	0.004
	(2.02)[b]	(2.13)[b]	(2.04)[b]	(1.84)[c]
Long-term elasticities				
Foreign BERD	0.265	0.446[a]	0.343	0.542[a]
Domestic BERD	0.434[a]	0.325[a]	0.500[a]	0.361[a]
Domestic HERD	0.229[b]	0.060[b]	0.243[b]	0.056[c]
Adjusted R^2	0.38	0.27		
S.E. of regression	0.020	0.019		

Note: All regressions were estimated in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged and their first difference terms were also included in the estimation. We have not reported the results for first difference terms in the table. T-ratios are in parentheses; t-statistics for FGLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D. HERD is higher education expenditure in R&D.

Long-term elasticities are estimated as follows: for variable X (X = foreign BERD, domestic BERD and domestic HERD), divide the estimated coefficient for X by the opposite of estimated coefficient for lagged labor productivity in the same regression. For example, in the first regression (column 1), the long-term elasticity for foreign BERD is 0.022/0.083 = 0.265.

[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significant at 10 percent level

Table 3. Effects of government R&D and business R&D on labor productivity growth
Dependent variable is change in log labor productivity
Number of observations = 304 (sample period: 1981-2000)

	FGLS	SUR	2SLS	3SLS
Lagged labor productivity	-0.117	-0.107	-0.094	-0.094
	(-3.89)[a]	(-9.38)[a]	(-3.65)[a]	(-8.45)[a]
Business cycle	0.260	0.152	0.275	0.165
	(2.95)[a]	(10.68)[a]	(3.69)[a]	(11.51)[a]
Investment intensity	0.063	0.044	0.055	0.034
	(4.63)[a]	(9.39)[a]	(3.65)[a]	(6.49)[a]
Population growth	-0.009	-0.006	-0.010	-0.006
	(-1.57)	(-3.12)[a]	(-1.64)	(-2.66)[a]
Openness	0.028	0.019	0.033	0.019
	(2.07)[b]	(3.11)[a]	(2.68)[a]	(2.90)[a]
Germany dummy	-0.044	-0.037	-0.038	-0.034
	(-2.30)[b]	(-9.59)[a]	(-2.14)[b]	(-9.03)[a]
Foreign BERD	0.001	0.005	0.003	0.002
	(0.03)	(0.60)	(0.13)	(0.25)
Domestic BERD	0.028	0.032	0.028	0.031
	(3.75)[a]	(16.73)[a]	(4.19)[a]	(15.59)[a]
Domestic GOVERD	0.006	-0.022	0.004	-0.021
	(0.78)	(-7.16)[a]	(0.57)	(-6.65)[a]
Long-term elasticities				
Foreign BERD	0.009	0.046	0.032	0.021
Domestic BERD	0.239[a]	0.299[a]	0.298[a]	0.330[a]
Domestic GOVERD	0.051	-0.206[a]	0.043	-0.223[a]
Adjusted R^2	0.30	0.27		
S.E. of regression	0.020	0.019		

Note: All regressions were estimated in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged and their first difference terms were also included in the estimation. We have not reported the results for first difference terms in the table. T-ratios are in parentheses; t-statistics for FGLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D and GOVERD is government expenditure in R&D.

Long-term elasticities are estimated as follows: for variable X (X = foreign BERD, domestic BERD and domestic GOVERD), divide the estimated coefficient for X by the opposite of estimated coefficient for lagged labor productivity in the same regression. For example, in the first regression (column 1), the long-term elasticity for foreign BERD is 0.001/0.117 = 0.009.

[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significant at 10 percent level

Table 4. Effects of business R&D on labor productivity growth (with longer sample)
Dependent variable is change in log labor productivity
Number of observations = 411 (sample period: 1973-2000)

	FGLS	**SUR**	**2SLS**	**3SLS**
Lagged labor productivity	-0.065	-0.067	-0.045	-0.046
	(-4.39)[a]	(-6.18)[a]	(-2.95)[a]	(-4.45)[a]
Business cycle	0.480	0.439	0.521	0.506
	(7.47)[a]	(9.92)[a]	(8.59)[a]	(11.19)[a]
Investment intensity	0.044	0.039	0.020	0.002
	(4.26)[a]	(4.73)[a]	(1.65)[c]	(0.21)
Population growth	-0.005	0.001	-0.003	0.004
	(-1.00)	(0.18)	(-0.75)	(1.33)
Openness	0.035	0.040	0.047	0.048
	(3.61)[a]	(6.85)[a]	(5.04)[a]	(7.67)[a]
Germany dummy	-0.010	-0.016	-0.012	-0.018
	(-1.21)	(-3.10)[a]	(-1.37)	(-3.11)[a]
Foreign BERD	0.036	0.032	0.035	0.018
	(1.81)[c]	(3.01)[a]	(1.74)[c]	(1.53)
Domestic BERD	0.028	0.019	0.024	0.016
	(5.11)[a]	(6.65)[a]	(4.55)[a]	(4.90)[a]
Long-term elasticities				
Foreign BERD	0.554[c]	0.478[a]	0.778[c]	0.391
Domestic BERD	0.431[a]	0.284[a]	0.533[a]	0.348[a]
Adjusted R^2	0.38	0.27		
S.E. of regression	0.018	0.018		

Note: All regressions were estimated in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged and their first difference terms were also included in the estimation. We have not reported the results for first difference terms in the table. T-ratios are in parentheses; t-statistics for GLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D.

Long-term elasticities are estimated as follows: for variable *X* (*X* = foreign BERD and domestic BERD), divide the estimated coefficient for *X* by the opposite of estimated coefficient for lagged labor productivity in the same regression. For example, in the first regression (column 1), the long-term elasticity for foreign BERD is 0.036/0.065 = 0.554.

[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significance at 10 percent level

Table 5. Sectoral decomposition of business R&D effects on labor productivity growth
Dependent variable is change in log labor productivity
Number of observations = 402 (sample period: 1973-2000)

	FGLS	SUR	2SLS	3SLS
Lagged labor productivity	-0.084	-0.082	-0.063	-0.064
	(-4.71)[a]	(-6.87)[a]	(-3.84)[a]	(-5.67)[a]
Business cycle	0.529	0.509	0.576	0.570
	(8.36)[a]	(11.96)[a]	(9.65)[a]	(12.93)[a]
Investment intensity	0.048	0.035	0.022	0.002
	(4.48)[a]	(4.25)[a]	(1.80)[c]	(0.19)
Population growth	-0.005	0.003	-0.004	0.005
	(-0.93)	(1.08)	(-0.95)	(1.66)
Openness	0.041	0.042	0.050	0.050
	(3.91)[a]	(5.96)[a]	(4.89)[a]	(6.76)[a]
Germany dummy	-0.013	-0.016	-0.013	-0.015
	(-1.41)	(-3.24)[a]	(-1.44)	(-2.76)[a]
Foreign BERD	0.057	0.039	0.051	0.025
	(2.86)[a]	(3.57)[a]	(2.46)[b]	(2.09)[b]
BERD in HTM	0.011	0.011	0.010	0.009
	(3.09)[a]	(4.61)[a]	(2.75)[a]	(3.42)[a]
BERD in MHTM	0.009	0.008	0.007	0.009
	(1.80)[c]	(2.29)[b]	(1.58)	(2.66)[a]
BERD in MLTM	0.012	0.008	0.012	0.007
	(2.99)[a]	(2.89)[a]	(2.90)[a]	(2.68)[a]
BERD in LTM	-0.004	-0.006	-0.003	-0.006
	(-1.35)	(-2.70)[a]	(-1.04)	(-2.62)[a]
BERD in services	-0.002	-0.001	-0.001	-0.001
	(-1.44)	(-1.24)	(-0.86)	(-1.35)

Note: All regressions were estimated in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged and their first difference terms were also included in the estimation. We have not reported the results for first difference terms in the table. T-ratios are in parentheses; t-statistics for GLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D; HMT is high-tech-manufacturers; MHTM is medium-high-tech manufacturers; MLTM is medium-low-tech-manufacturers; LTM is low-tech manufacturers.

[a] indicates significance at 1 percent level; [b] indicates significance at 5 percent level; [c] indicates significance at 10 percent level.

When we restricted the sample from 1979 to 2000, there were no changes in the sign of the coefficients, but there were changes in the level of significance. Specifically, the positive point estimate of MHT turned insignificant and the negative point estimate of services turned significant.

Table 5 (contd.). Long Run Elasticities

	FGLS	SUR	2SLS	3SLS
Foreign BERD	0.679[a]	0.476[a]	0.809[b]	0.391[b]
BERD in HTM	0.131[a]	0.134[a]	0.159[b]	0.141[a]
BERD in MHTM	0.107[c]	0.098[b]	0.111	0.141[a]
BERD in MLTM	0.143[a]	0.098[a]	0.190[a]	0.109[a]
BERD in LTM	-0.048	-0.073[a]	-0.048	-0.094[a]
BERD in services	-0.024	-0.012	-0.016	-0.016

Long-term elasticities are estimated as follows: for variable *X* (*X* = foreign BERD, BERD in HTM, BERD in MHTM, BERD in MLTM, BERD in LTM and BERD in services), divide the estimated coefficient for *X* by the opposite of estimated coefficient for lagged labor productivity in the same regression.
[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significance at 10 percent level

Table 6. Decomposition of long-term elasticities into sectoral R&D intensity and size
Dependent variable is change in log labor productivity
Number of observations = 323 (sample period: 1979-2000)

	GLS	SUR
Foreign BERD	0.328[c]	0.201[b]
Elasticities of R&D intensities		
BERD in HTM	0.112[b]	0.007
BERD in MHTM	-0.009	0.007
BERD in MLTM	0.086[b]	0.049[a]
BERD in services	-0.034[a]	-0.014[b]
Elasticities of value added share		
BERD in HTM	0.345[a]	0.264[a]
BERD in MHTM	-0.103	-0.021
BERD in MLTM	-0.267[b]	-0.368[a]
BERD in services	-0.862[c]	-1.076[a]

Note: The sample used for this regression was from 1979 to 2000. The elasticities are based on regression using (R3) where all variables enter in log forms and have country and time dummies included. All domestic and foreign R&D variables were lagged in the estimation. Note that among the variables mentioned in (R3), population growth and German dummy were not used in estimation, as these variables were not significant. We have not also included the variables in first difference as regressors. The statistical tests are based on the T-ratios of the variables. The t-statistics for GLS specification are computed from hetroscedasticity-consistent standard errors and covariance.

BERD is business expenditure in R&D; HTM is high-tech-manufacturers; MHTM is medium-high-tech manufacturers; MLTM is medium-low-tech-manufacturers; LTM is low-tech manufacturers.
[a] indicates significance at 1 percent level
[b] indicates significance at 5 percent level
[c] indicates significance at 10 percent level

Appendix 1. Data

Labor productivity

For labor productivity data, we use the series "real GDP chain per worker at 1996 prices" from Penn World Table (PWT). For Germany, these data are not available prior to 1991 in PWT. However, they are available from OECD's Strucutral Analysis (STAN) database since 1980, which is indexed to 100 in 1995. We use both PWT and STAN to compute the value of labor productivity for Germany from 1980 to 1990. For this purpose, we multiplied the ratio of each year's index from 1980 to 1990 to index in 1995 (using STAN database) by the labor productivity data (from PWT) in 1995 and took that value as data on labor productivity for each year.

R&D data

All R&D data are intramural R&D, that is, the R&D expenditure done within the reporting sector, including expenses incurred by other sectors.

Even at the aggregate level, for some countries, data for some intervening years were not available. In that case, we took the average of two years, one before and one after, and filled the gap. In a couple of instances, the data were not available for two consecutive years; in this case, we took the average of two closest years.

For Belgium, the data on R&D for years 1981 and 1982 are not available. In this case, we computed the growth rates in 1984 based on 1983. We discounted the value of R&D expenditure of 1983 by this growth rate and assumed that to be the figure for 1982. Similarly, by discounting the value of 1982 by the same growth rate, we estimated the R&D expenditure for year 1981.

For industry level R&D, we used data from 1973 to 2001 from the Analytical Business Enterprise R&D (ANBERD) database of OECD. As the name suggests, this database covers only business R&D (not government and higher education R&D), and the data are available only at current price in PPPs. Since there are no separate deflators for R&D, we used GDP deflators using current and constant-price GDP of sample countries from OECD database to convert them into constant dollars. Furthermore, for Belgium, we have BERD data by industry only for the period of 1987 to 2000. For Denmark, the data for 2000 were missing, in which case we used the average of four years (1998, 1999, 2001 and 2002).

Data for Norway for 1994 were not available according to ISIC Rev 3. We used data on ISIC Rev. 2 with appropriate concordance. Similarly, the data for Germany by industry at ISIC Rev. 3 starts only from 1995. Hence, from 1991 to 1995, we used data from ISIC Rev. 2 with concordance; prior to 1991, we used data for West Germany at ISIC Rev. 2. Finally, the data on ISIC Rev. 3 for Italy were available only from 1991. Prior to that, we used data on ISIC Rev. 2.

Foreign R&D

In computing the foreign R&D expenditure variable, we more or less follow Coe and Helpman (1995). More specifically, foreign R&D expenditure for country *i* for year *t* is calculated as a weighted sum of sample countries' domestic R&D expenditure such that

$$r_{it}^{*} = \sum_{j=1, j \neq i}^{15} \frac{1}{y_{jt}} m_{ij} r_{jt} \qquad i = 1, \ldots, 16 \qquad \text{and } j = 1, \ldots, 16.$$

where m_{ij} is country *i*'s share of imports from country *j* relative to its total imports from 15 sample foreign countries; r_{it}^{*} is the amount of foreign R&D expenditure in country *i*; r_{jt} is the amount of business R&D expenditure in country *j;* and y_{jt} is country *j*'s GDP (both measured in constant-price PPP). Real GDP is obtained by using two PWT series, the constant-price GDP per capita in PPP multiplied by population.

Appendix 2. Classification of manufacturing industries based on technology

ISIC Rev.3	Descriptions	Technology type
15...37	**Total Manufacturing**	
15+16	Food products, beverages and tobacco	LTM
17...19	Textiles, textile products, leather and footwear	LTM
20...22	Wood, paper, printing, publishing	LTM
23	Coke, refined petroleum products and nuclear fuel	MLTM
24-2423	Chemicals excluding pharmaceuticals	MLTM
2423	Pharmaceuticals	HTM
25	Rubber and plastics products	MLTM
26	Other nonmetallic mineral products	MLTM
27	Basic metals	MLTM
28	Fabricated metal prod. (exc. mach. and equip.)	MLTM
29	Machinery and equipment nec	MHTM
30	Office, accounting and computing machinery	HTM
31	Electrical machinery and apparatus nec	MHTM
32	Radio, TV and communication equipment	HTM
33	Instruments, watches and clocks	HTM
34	Motor vehicles	MHTM
351	Building and repairing of ships and boats	MLTM
353	Aircraft and spacecraft	HTM
352+359	Railroad and other transport equipment nec	MHTM
36+37	Furniture, manufacturing nec and recycling	LTM
40+41	**Electricity, gas and water**	
45	**Construction**	
50...99	**Total services**	SERVICES

Note: HTM stands for high-tech manufacturers; MHTM stands for medium-high-tech manufacturers; MLTM stands for medium-low-tech manufacturers; TM stands for low-tech manufacturers; and S stands for services.

The short form “nec” means “not else classified”