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Abstract

In this paper we explore variables that may have an impact on multifactor productivity (MFP) in the long-run using the KLEMS database for Canada. We estimate a dynamic heterogeneous panel error-correction model of twelve 2-digit level industries. Variables investigated include ICT capital, outsourcing, competition, trade openness, public infrastructure, and R&D. Results suggest that over the 1976 - 2003 period ICT capital services, outsourcing and trade all had a positive impact on the level of industry MFP. The speed of adjustment varies significantly by industry.

JEL classification: C23, D24, O30
Bank classification: Productivity

Résumé

À partir de données canadiennes de la base KLEMS, les auteurs analysent les variables susceptibles d'influer sur la productivité multifactorielle à long terme. Ils estiment pour ce faire un modèle à correction d'erreurs fondé sur des données de panel hétérogènes et dynamiques concernant douze secteurs à deux chiffres. Six variables sont étudiées : les services du capital lié aux technologies de l'information et de la communication (TIC), l'externalisation, la concurrence, l'ouverture au commerce extérieur, les infrastructures publiques et la recherche-développement. Selon les résultats obtenus, de 1976 à 2003, les services du capital TIC, l'externalisation et l'ouverture au commerce extérieur ont tous eu une incidence positive sur la productivité multifactorielle dans les secteurs considérés. Le rythme d'ajustement de celle-ci varie considérablement d'un secteur à l'autre.

Classification JEL : C23, D24, O30
Classification de la Banque : Productivité

1 Introduction

Multifactor productivity (MFP) has played a significant role in driving long-term fluctuations in labour productivity growth in Canada over the past four decades.[1] Given the importance of MFP, it is important to understand its long-run determinants. Although recent interest has centered around information and communications technologies (ICT), the literature also provides a long list of other possible determinants, such as R&D capital, R&D spillover, competition, global trade openness, outsourcing and public infrastructure.

Using data on 12 Canadian industries (that covers the entire business sector) for 1976-2003, this paper employs recent panel cointegration techniques to establish the relative importance of these long-run determinants of MFP. This paper contributes to the literature in three ways. First, it is one of the few studies for Canada that investigate ICT's potential impact on MFP at the aggregate or industry level. While there is a growing body of research for the United States and the United Kingdom, Canadian studies are limited to Leung (2004) and Rao et al. (2007).[2] Second, most studies tend not to be comprehensive, but rather one or two determinants are examined at a time in each study. This study considers all the factors mentioned above, thereby reducing the chance of overstating the importance of any one factor. Third, the main results of the paper are based on Pesaran et al.'s (1999) Pooled Mean Group (PMG) estimator. The advantage of using this particular estimator is that it allows the long-run relationship between MFP and its determinants to be efficiently estimated, while allowing for industry-specific short-run impacts that are different from the long-run effects. This effectively deals with the problem of the long and variable lags associated with the effect of ICT investment and possibly other determinants on MFP. To our knowledge, the PMG estimator or other panel cointegration techniques have not yet been

[1] Long-term labour productivity growth in Canada went through three distinct phases over the 1961-2006 period. A period of strong growth between 1961 and 1980 was followed by weak growth between 1980 and 1996. Since 1996, labour productivity growth has accelerated, albeit not to the level seen in the first period. Using a growth accounting procedure, Baldwin and Gu (2007) find that a large fraction of the decline in labour productivity growth and the entire recent acceleration was due to changes in multifactor productivity (MFP) growth.

[2] See Basu and Fernald (2007), O'Mahoney and Vecchi (2005), and Basu et al (2003) for evidence from the United States and the United Kindgom.

applied in a Canadian study of the determinants of MFP.

After controlling for some factors that drive a wedge between measured MFP and its interpretation as a measure of technical efficiency, it is found that ICT capital, outsourcing and trade have a statistically significant positive effect on MFP. However, the long-run impact of ICT is found to be small. This could partly be due to the fact that ICT is a relatively new type of capital, the stock of which did not increase strongly until the 1990s. It could be that the incremental increases in ICT capital pre-1990 were not large enough to enable the wholesale changes in the organization of production or the development of network externalities that drive MFP growth. Limiting the sample to more recent years is not currently possible because of the paucity of the data, but a test of this hypothesis could be carried out when more disaggregated industry data or a longer time series becomes available. Furthermore, to the extent that ICT has facilitated increases in outsourcing and trade, these other determinants may be indirectly capturing some of ICT's effect on MFP.

The paper is organized as follows: section 2 highlights the contribution of the current paper relative to the literature, section 3 briefly outlines the PMG estimator, the data and discusses preliminary econometric issues that must be resolved before estimation takes place. The main results are presented in section 4, and section 5 provides some concluding remarks.

2 Related Literature

Factors such as ICT, R&D capital, R&D spillover, foreign direct investment, trade openness, outsourcing/offshoring, public capital, labour quality, machinery & equipment intensity, and MFP gap relative to the frontier have been posited to affect MFP. Perhaps because of the timing of the surge in ICT investment and the rebound in MFP growth in the 1990s, ICT has attracted much attention recently. As a general purpose technology, ICT is believed to have made possible changes in organizational structures that have raised MFP.[3] Despite this

[3] See Milgrom and Roberts (1990), Brynjolfsson and Hitt (2000a) and Stiroh (2002), for example. In addition, Fuss and Waverman (2005) also argue that the increased use of ICT has led to the development of

attention, studies of the Canadian experience have been limited to Leung (2004) and Rao et al. (2007). Using aggregate data, Leung (2004) finds that growth in computer investment has a positive, but lagged effect on MFP growth. Unfortunately, a major drawback of this study is that it is based on a relatively small number of annual observations. This drawback is a problem faced by almost all similar studies. Since ICT capital is relatively new, its effect is likely concentrated in the most recent years. To get around this problem, firm-level data or detailed industry data have often been used. Still, most evidence of the effect of ICT on MFP is for the U.S. where the investment in ICT started the earliest and has been the strongest.

Rao et al. (2007) use industry-level panel data similar to those used in this paper and corresponding U.S. data to study the impact of the degree of ICT capital intensity (stock per worker) on MFP growth. They do not find, however, any evidence that supports ICT intensity as a determinant of MFP growth in either country. This result could be due to the fact that only the contemporaneous relationship between ICT and MFP is studied in Rao et al. (2007). As suggested in Leung (2004) and a number of international studies, there could be lags in the relationship between ICT and MFP.[4] Moreover, disruption costs associated with installing a new type of capital may even have an initial negative effect on MFP in the short-run. The negative finding of Rao et al (2007) could also be due to the fact that they give each industry the same weight in their regressions. It could be the case that there are some industries where the changes in MFP are particularly difficult to explain, such as the long-term declines in MFP observed in some service industries.[5] The PMG estimator used in this paper effectively deals with both of these issues. It deals with the first issue

network externalities.

[4]For example, Basu et al. (2003) finds a positive relationship between ICT capital growth in the 1990-1995 period and MFP growth in the 1995-2000 period using U.S. industry data. Brynjolfsson and Hitt (2002a, b) finds evidence of lagged effect of ICT of up to five years in U.S. establishment-level data, and Zwick (2003) finds evidence of a lagged effect of three years using German establishment level data. Still, even after considering the lagged effects, the evidence of ICT's relation to MFP remains somewhat mixed. For example, Basu et al. (2003) do not find evidence of lagged effects when they examine U.K. data. See also Bosworth and Triplett (2007) , Corrado et al. (2007) and Oliner et al. (2007).

[5]This and other measurement issues prompt Basu et al. (2003) and Basu and Fernald (2007) to split their sample into well-measured and less-well measured industries.

by estimating the long-run relationship between ICT and MFP, at the same time allowing for a possible negative relationship in the short-run. It deals with the second issue, as one of the properties of the PMG estimator is its robustness to outliers; it gives less weight to industries where the relationship of interest is less well-estimated (has larger standard errors). O'Mahony and Vecchi (2005) have used this approach on U.S. and U.K. industry data[6], but this is the first paper using Canadian data that applies the PMG estimator in examining the determinants of MFP.

Furthermore, whereas O'Mahony and Vecchi concentrate on the impact of ICT on output, this paper also considers factors other than ICT to explain MFP. For example, R&D has been found to stimulate innovation, and to enhance the absorptive capacity of its performers and promotes technology transfers both across industries and national borders – all leading to the growth of MFP.[7,8]

One way in which technology transfers can occur is through trade in services and embodied products. Restrictions that inhibit trade could limit innovation. Furthermore, it has been argued that trade restrictions could deter competition and stunt productivity growth, and that the inability to service international markets prohibits the achievement of economies of scale (which would be picked up by usual measures of MFP).[9]

Related to the effect of trade openness is the impact of outsourcing and offshoring. Theoretically, firms may experience productivity improvements if they focus on core competencies or even expand output by contracting out relatively inefficient activities. The benefits of outsourcing on aggregate productivity may be realized through product and labour specialization, economies of scale and restructuring, and innovation.[10] While there have been

[6] Their findings suggest a strong impact of ICT on MFP in the United States, and a weaker impact in the United Kingdom.

[7] Examples of studies looking into the impact of R&D on MFP include: Griliches (1980, 1992, 1994), Grilliches and Lichtenberg (1984), Coe and Helpman (1995), Berstein (1996), Hanel (2000), Guellec and van Pottelsberghe (2001), Griffith et al. (2004) and Hignon (2004).

[8] While part of the labour input and software related to R&D activities are captured in the System of National Accounts, R&D capital is not accounted for in the calculation of MFP as a Solow residual.

[9] Papers that link the trade openness of a country or industry to productivity performance include: Coe et al (1997), Baldwin and Gu (2004) and Winters (2004).

[10] For instance, the Survey of Innovation 2005 shows that innovative manufacturing plants are more likely to participate in the global supply chain than non-innovative plants and that plants that form part of the

heated debates on the impact of outsourcing and offshoring (a special form of the former, when the external provider is located abroad) on labour market outcomes, empirical research on their productivity impacts has been scarce and results have been mixed.[11]

Research has also suggested that competition generally promotes efficiency gains (via "creative destruction" for instance) and technological diffusion — both of which eventually lead to improvement in factor productivity.[12] The relationship between competition and innovation has been controversial. Standard industrial organization theory suggests a negative relation due to reduced monopoly rents for innovators while most empirical evidence points to the contrary.[13] Aghion et al. (2005) explains this discrepancy with a model where the relationship between competition and innovation is inverted U-shaped . Industries with little competition will not innovate much since firms can earn high profits even without having to innovate. Innovation will also be low in industries where there is so much competition that followers are discouraged by their inability to reap profits and the leader does not have to innovate much harder in order to retain the lead. Therefore innovation will most likely take place at some intermediate degree of competition.

Finally, like R&D capital, another type of omitted capital is public infrastructure. Transportations system, water and sewage systems clearly facilitate production but are generally not included in calculations of industry MFP.[14]

Although there are many empirical studies that find links between the factors mentioned above and MFP, most focus on one or two factors at a time. However, many of these factors are strongly related. R&D spillover may be facilitated by trade. Trade may stimulate competition. International outsourcing may be facilitated by ICT investment and improvements in supply chain management. Therefore, empirical investigations that focus solely on the contribution of one factor likely have overstated the importance of that factor. While

global supply chain are more prone to have world-first innovations than their non-participating counterparts.

[11] See Olsen (2006) for a review.

[12] See Pilat (1996) and Baldwin and Gu (2004).

[13] See for example Nickell et al. (1997).

[14] Nadiri and Mamuneas (1994) and Harchaoui and Tarkhani (2003) find empirical evidence for the U.S. and Canada, respectively, that public infrastructure contributes to the growth of MFP in that it reduces the cost of production, stimulates output expansion (with elastic demand) and complements private capital.

not fully comprehensive because of data constraints, this paper takes into account many of posited determinants.[15]

3 Econometric Framework and Data

3.1 *Econometric Framework*

The long-run impact of the determinants of MFP is identified using the Pooled Mean Group (PMG) estimator developed in Pesaran et al (1999). The PMG estimator uses maximum likelihood to estimate an error correction mechanism where the long-run coefficients are constrained to be identical across industries, but the short-run dynamics (including the speed of adjustment) and the error variances are allowed to differ. Specifically, the following error correction model (ECM), re-parameterized from an ARDL$(p, q, q, ..., q)$ model, is estimated:

$$\Delta y_{i,t} = \phi_i (y_{i,t-1} - \boldsymbol{\theta}' \mathbf{x}_{i,t}) + \sum_{j=1}^{p-1} \lambda_{i,j} \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \boldsymbol{\delta}'_{i,j} \boldsymbol{\Delta} \mathbf{x}_{i,t-j} + urate_t + \mu_i + \varepsilon_{it}, \qquad (1)$$

where i indexes industries, t indexes time, $\mathbf{x_{it}}$ is a vector of (weakly exogenous) regressors, μ_i is a fixed effect, and ε_{it} is a error term that is independently distributed across i and t.[16]A control for cyclical effects, $urate_t$, is also included in the model.[17] This proxy for utilization, defined as one minus the aggregate unemployment rate, is applicable to all industries whereas the traditional capacity utilization rates are not available for services industries. It is preferable to the output gap measure as the latter relies on assumptions about productivity growth, which if used may introduce simultaneity biases into our model.

[15]For example, the industry groupings for which data on foreign direct investment is available cannot be easily mapped into the industry categories used by the other data. Foreign direct investment is seen as one of the most efficient conduits of technological transfer between countries. Papers on the role of foreign direct investment include: Globerman (1979), Bernhardt (1981), Gera et al. (1999) and Lileeva (2006).

The time period in which the data is available is another limiting factor. For example, the R&D variables are available only from 1987 onwards.

[16]In practice, the assumption of weakly exogeneity and no serial correlation in the error terms can be satisfied by adding a sufficient number of lags to the model.

[17]Paquet and Robidoux (2001) show that the statistical properties of measured MFP change after adjusting for variable input utilization, and Leung (2004) shows that measured MFP is related to computer investment only after it is has been adjusted for variable input utilization.

Alternatives to the PMG estimation of the ECM include: Seemingly Unrelated Regressions (SUR) where contemporaneous error correlations are accounted for; dynamic fixed effect (DFE) estimation where all coefficients, except the fixed effect, are assumed to be homogenous across industries; and the mean-group (MG) estimator where all coefficients are allowed to vary by industry and an average across industries is calculated.[18] The PMG estimator can be viewed as an intermediate estimator between DFE and MG that balances the properties of consistency and efficiency; the dynamic fixed effect estimator is consistent and efficient if the assumption of homogeneity is valid. However, the restriction of common short-run dynamics may be too strong. The mean group estimator is consistent but not efficient if indeed some of the parameters are not significantly different from each other across the industries.[19]

3.2 *Data Description*

The majority of the data for this study came from the KLEMS database compiled by Statistics Canada. This database provides time series data on the value and prices of gross and value-added output, capital (ICT vs. Non-ICT), labour and intermediate (energy, materials, and services) inputs for industries based on the 1997 North American Industry Classification System (NAICS).

MFP for each industry i at year t is obtained as the conventional growth accounting residual assuming perfect competition and constant returns to scale:

$$MFP_{i,t} = \frac{Y_{i,t}}{K_{i,t}^{\overline{\sigma_{i,t}^{k}}} L_{i,t}^{\overline{\sigma_{i,t}^{L}}} U_{i,t}^{\overline{\sigma_{i,t}^{U}}}}, \tag{2}$$

[18]If only the estimates of the long-run coefficients are of interest, other alternatives to PMG would be the Dynamic OLS estimator (see Mark and Sul (2003)) and the Fully-Modified OLS estimator (see Pedroni (2000)). There is no study that compares the small-sample properties of these three estimators. Besides the estimation of the short-run dynamics and speed of adjustment, another advantage of the PMG estimator is that a Hausman test can be used to test the homogeneity of the long-run coefficients. All three estimators assume cross-sectional independence of the error terms.

[19] There is reason to think that industry-specific factors may affect the long-run rate of return of various factors. However, the limited size of the sample we study prohibits a separate analysis of each of the long-run coefficents for each industry.

where Y is gross output, K is capital input, L is labour input,[20] U is intermediate input, all in chained 2002 dollars. The weights, $\overline{\sigma^j}(j = K, L, U)$ are two-period average shares of nominal factor cost in total cost.

We consider the following industry-specific variables as potential long-run determinants of MFP:

- *ICT capital services*
- *R&D intensity (RDI),* calculated as the ratio of R&D expenditure to gross output, or alternatively *R&D stock (RD)* as the accumulated amount of depreciated real R&D expenditure according to a perpetual inventory model, and *R&D spill-over (SRD)* as input-share weighted real R&D stocks of the domestic supplier industries for each sector. There is considerable uncertainty around the appropriate rate of R&D depreciation, hence the imprecision of the RD and SRD series. This study uses a depreciation rate of 10%.[21] Data on FDI that correspond to the industry classification system we use are not available and as a result the effect of international R&D spill-over is omitted.
- *Public infrastructure (infra_g) or mass infrastructure (infra_m)*: The common definition of public infrastructure refers to the stock of engineering capital (such as high-ways, roads, bridges, water and sewage systems) owned by the public sector (governments and most health and education services in Canada). However, the transportation and utilities sectors also own vast amounts of engineering capital (vessels, electricity generators, gas distribution lines for example) that exhibit similar characteristics to "public goods" in that they serve the public and are generally *non-excludable* and *non-rivalrous*. We therefore include in this study a variant of public infrastructure – mass infrastructure – that includes both the traditionally defined public infrastructure and the engineering capital stock of the two afore-mentioned sectors.[22]
- *Outsourcing,* defined as the ratio of intermediate input costs (purchased energy, materials and services) over nominal gross output.
- *Global trade openness,* defined as the sum of nominal world imports plus exports divided by world output, based on data from the IMF. The use of a global rather than industry-specific trade openness measure is dictated by data constraints. This more exogenous variable likely captures several facets of globalization such as offshoring and the FDI stock.

[20] Note that labour quality is explicitly taken into account in the measurement of labour supply in the Canadian productivity accounts. Therefore it need not be one of the MFP determinants.

[21] Higon (2004) also used a depreciation rate of 10 percent, while Guellec et al. (2001) assumed 15 percent. Coe and Helpman (1995) showed that results are generally not sensitive to the choice of this rate.

[22] Indeed, over the 1961 – 2006 period, utilities and transportation and warehousing accounted for 46% of net engineering stock in Canada (excluding mining and oil and gas components), more than the share of the public counterpart (41%).

- *Markup*, as a reverse indicator of competition. Two markup measures are examined in this study. One is price-over-average-variable-cost ratio (*markup1*)calculated as nominal gross output divided by nominal variable costs (labour plus intermediate input) – the average variable cost is used as a proxy for marginal cost under the assumption of constant returns to scale. The second markup measure, *markup2*, is based on a state-space model described in Leung (2007) .

More details on the source and construction of these and other variables can be found in Appendices 1 and 2.

The ideal data set for our study would comprise three-digit NAICS industries spanning as long a time period as possible, given the large number of variables of interest. However, data availability issues restricted the coverage to just 12 industries over 28 years (1976 – 2003), as follows[23]:

- Agriculture, Forestry, Fishing and Hunting (NAICS 11)
- Mining, Oil and Gas Extraction (NAICS 21)
- Utilities (NAICS 22)
- Construction (NAICS 23)
- Manufacturing (NAICS 31 – 33)
- Wholesale Trade (NAICS 41)
- Retail Trade (NAICS 44 – 45)
- Transportation and Warehousing (NAICS 48 – 49)
- Information and Cultural Industries (NAICS 51)
- Finance, Insurance, Real Estate and Leasing (FIREL, NAICS 52 – 53)
- Professional, Scientific and Technical Services (NAICS 54)
- Other Services Except Public Administration (NAICS 56 – 81)

Table 2 presents the average annual growth rates, as measured by the log first difference, of key variables for the twelve industries. Over the 1976 – 2003 period, MFP trended upwards for eight industries and downwards for four, with annual growth ranging from -1.4

[23]Derived R&D data date back to 1987 only.

percent (Professional, Scientific and Technical Services) to 1.2 percent (Wholesale Trade). ICT capital services grew rapidly for all industries, at around 20 percent per annum, except for Information and Cultural Industries which saw a 7.3 percent annual growth rate. Outsourcing, trade openness, infrastructure and R&D variables generally exhibit an increasing pattern over time. The markup measures, like MFP, show more variation by industry.

3.3 *Unit Root Tests and Cointegration*

Our main objective is to explore the long-run relationship between the level of MFP and a wide range of variables of interest. If all the variables are stationary, one could regress MFP directly on potential explanatory variables using standard panel data techniques such as pooled OLS. However, in the case where stochastic trends are present, a spurious regression problem may exist and the results may be highly misleading. While differencing can sometimes address the problem caused by $I(1)$ variables, it inevitably eliminates information for the long-run, which is precisely what we are after. A more suitable approach – should all variables turn out to be $I(1)$ and cointegrated – is an error-correction-model (ECM) suitable for a panel.

To test for the order of cointegration of the data, we apply three panel unit root tests: IPS by Im-Pesaran-Shin (2003), Hadri (2000) and cross-section augmented Dickey-Fuller (CADF) by Pesaran (2003). Under the null hypothesis of the IPS t-bar test, all series in the panel contain a unit root.[24] The Lagrange Multiplier (LM) test of Hadri (2000) differs from IPS in that it tests against the null of stationarity.[25] Both the IPS and Hadri tests belong to the category of so-called "first generation" tests developed on the assumption of cross-sectional independence of error terms. However, macroeconomic time series of different industries can

[24] Under the alternative, a fraction of the series are assumed to be stationary with potentially heterogeneous autoregressive parameters. The IPS t-bar test is based on the average of the t-statistic from the individual augmented Dickey-Fuller (ADF) tests across the panel.

[25] The series are assumed to be stationary around a unit-specific level (i.e. fixed effect) or a unit-specific deterministic trend. The error process may be assumed homoskedastic or heteroskedastic across units. In addition, serial correlation in disturbances can also be accounted for using a Newey-West estimator of the long-run variance.

be contemporaneously correlated. Pesaran (2003) , among others, has suggested a simple modification of the ADF test (CADF) in the case where a single unobserved common factor captures cross-sectional error dependence.[26]

Table 3 presents the result of unit root tests. In addition to the three panel tests just discussed, the augmented Dickey-Fuller and Phillips-Perron tests for single time series are employed to test for unit root in variables that do not vary across units. All tests confirm that virtually all of the variables are non-stationary. The only exception is R&D intensity for which the null of unit root can be weakly rejected at the 10% level according to the IPS test. For the purpose of this study we treat R&D intensity as $I(1)$. Further tests on the first difference of these same variables indicate that MFP, ICT capital services, outsourcing, markup (both measures) and trade openness are $I(1)$ variables while the public infrastructure variables are $I(2)$.

Next, we conduct panel cointegration tests to investigate whether there exists a stationary long-run relationship between MFP and other variables.

For the purpose of this paper, we adopt the tests developed by Pedroni (1999, 2004).[27] A total of seven residual-based tests are available for the null of no cointegration allowing for heterogeneity in the short-run dynamics and the long-run slope coefficients across individual members of the panel. The tests also include individual heterogeneous fixed effects and trend terms. The first four test statistics, termed the "panel statistics", are equivalent to testing

[26] Each of the individual ADF regressions is augmented by the lags and first difference of the cross-sectional mean of the dependent variable and the average of the individual CADF t-statistics can then be used to test the null of unit root. The CADF test is not appropriate if the non-stationarity of a variable is caused by unobserved common stochastic trends across units, because these common trends are removed by explicitly controlling for the cross-sectional mean. Nevertheless, we use CADF in addition to IPS and Hadri because of its ease of use, modest data requirements, and generally satisfactory finite sample properties. See Breitung and Pesaran (2005) for an evaluation of the various panel unit root tests.

[27] As is the case with unit root tests, the literature generally distinguishes between the "first" and recent generations tests of panel cointegration. The "first" generation typically ignores cross-sectional dependence due to global unobserved common factors, or partially accounts for them by cross-sectional de-meaning or by employing observable common effects such as oil prices. In addition, these tests tend to assume the existence of at most one cointegrating relation. More recent contributions to this literature tend to use a systems approach and places emphasis on accounting for cross-sectional dependence. However, research in the area of panel cointegration is still relatively new and a general approach addressing all the complications (heterogeneity, cross-sectional dependence, cross-unit cointegration, etc.) has yet to emerge. Breitung and Pesaran (2005) provides a comprehensive review of this subject.

against the alternative of a homogeneous autoregressive coefficient of the residuals from the cointegration regression. For the other three test statistics, called the "group statistics", no such homogeneity assumption is imposed under the alternative hypothesis.

We have six types of variables a subset of which[28] could form a cointegrating relation with MFP. In order to determine the specification of the cointegration vector, we adopt a general-to-specific approach using the criterion that all variables in the long-run equation are necessary for cointegration according to at least four out of the seven Pedroni (1999, 2004) tests at the 10% level or better. We start out with a cointegrating space that contains as many of the six types of variables as allowed by the time span of each. Should the null of no cointegration be rejected, variables are removed one at a time and the tests are re-run to see if the null is still rejected. This process continues until no more variable can be dropped without jeopardizing the cointegration. The most parsimonious specification includes the natural log of MFP, the natural log of ICT capital services, outsourcing, markup and trade openness. These variables form the $\mathbf{x_{it}}$ vector in equation (1). Table 4 reports the cointegration test results of this specification.

4 Results

This section focuses on the empirical results for the ECM as outlined in equation (1) using the pooled mean group (PMG) estimator. Our sample covers 12 Canadian industries at roughly the 2-digit NAICS level spanning the 1976 – 2003 period. The starting point is an ARDL model for each industry with lag orders chosen by the Schwarz-Bayesian Information Criterion (SBC) subject to a maximum lag of 3. Afterwards the homogeneity restriction is imposed and the maximum likelihood (ML) estimation using Newton-Raphson algorithm is carried out. Once the pooled ML estimates of the long-run parameters have been computed, the short-run coefficients including the industry-specific speed of adjustment can be

[28] ICT, outsourcing, markup, trade openness, infrastructure (first differenced), R&D intensity.

consistently estimated by running individual OLS regressions of the growth rate of MFP on the disequilibrium error and lagged differences of long-run determinants and other control variables.[29]

The overall fit of the ECM seems reasonably good. More than 65 percent of the variance in the logarithm of MFP is explained in four industries, and between 30 to 50 percent of the variance explained in seven other industries. The standard error of regressions ranges from 0.4 percent for manufacturing to 13.8 percent for utilities. At the conventional 5% level, there is no evidence of non-normal errors according to the Jarque-Bera test and only two of the twelve industries equations exhibited heteroskedasticity based on the Breusch-Pagan test. The Breusch-Godfrey test of residual serial correlation and the Ramsey RESET test of functional form indicate a problem of missing variables for certain industries. This is to be expected given the uncertain nature of explanatory variables for MFP that are not covered in this study. For those affected industries the coefficients are still unbiased as long as the missing variables are not significantly correlated with the included variables on the right-hand-side (unfortunately one cannot verify this). However, this makes inference about coefficients difficult.

With the aforementioned caveat in mind, we now proceed to discuss the main PMG results (Tables 5 & 6) regarding the long-run relationship between MFP and other variables, the speed of adjustment and short-run dynamics. This is followed by a comparison with results obtained using other estimation techniques. Finally we conclude this section by presenting the contribution from various factors in the model to the growth of MFP for a number of industries.

4.1 *Pooled Mean Group Results*

[29] The GAUSS code for conducting the PMG estimation was kindly provided by M. H. Pesaran.

4.1.1 ICT Capital

As expected, our result suggests that the impact of ICT on MFP in the long-run is positive and significant.[30] Table 2 shows that the average annual growth rate of ICT capital exceeded 20 percent in many industries, but even at that rate, the PMG estimates suggest ICT capital increased equilibrium MFP by only 0.04 per cent per year, *ceteris paribus*.[31] The rather small magnitude of the impact could be due to a number of factors. First, ICT is a relatively new type of capital, the stock of which did not increase noticeably until the 1990s. The accumulation of ICT capital prior to the 1990s may not have been substantial enough to induce dramatic accompanying changes in the organization of production. Or perhaps ICT capital in earlier times was not the right type to spur network externalities that drive MFP growth. Limiting the sample to more recent years would offer a better gauge of the degree of impact of ICT on MFP. Unfortunately one would need far more cross-sectional observations to make estimation valid.

Second, to the extent that ICT facilitates growth in outsourcing and by extension trade, the other determinants in the model could be indirectly capturing some of ICT's effect on MFP. Bartel et al (2005) posited a model to examine the channels by which technological changes (mostly ICT) can affect a firm's decision to outsource. An increase in the speed of technological advance increases outsourcing as the latter allows firms to take advantage of leading technologies without incurring the sunken costs of adoption. In addition, the adaptability and portability of skills associated with ICT generate a technological compatibility between a firm's use of its own technology and its ability to use others', therefore more ICT intensive firms face lower adjustments to outsourcing, which contributes to the positive relation between ICT and outsourcing. While it is beyond the scope of this paper to verify their model, our data do show that ICT moves closely with outsourcing. The correlation between demeaned levels of ICT and outsourcing is 0.65.

[30] In an alternative specification where industry-specific time trends are included, the coefficient on ICT turns out negative. It could be that the time trend acts as a proxy for the stochastic trend, in which case the negative coefficient is indicative of higher frequency comovements between MFP and ICT.

[31] The long-run elasticity of ICT with respect to MFP is 0.003 and 0.005 using the Mean Group and the SUR estimator, respectively.

4.1.2 Outsourcing

Outsourcing is found to be positively related to MFP, with a one percent increase in the degree of outsourcing raising MFP by 0.8 percent in the long run. This presents evidence that firms may experience productivity improvements if they focus on core competencies or even expand output by contracting out relatively inefficient activities. Benefits may be realized through product and labour specialization, economies of scale and restructuring. [32]

It is interesting to note that over the sample period (1976 – 2003) real purchased services grew by 5 percent annually in the business sector, almost twice as fast as the growth of outsourced materials and energy input. The tendency to outsource services was stronger in the services sector than in the goods sector. There may be a difference between the goods and services industries as to how their production processes benefit from an increasing degree of outsourcing of materials versus services. However, splitting our rather small sample into goods and services industries and further studying the impact of materials and services outsourcing separately would be impractical. Nonetheless, it would be a worthwhile endeavour in follow-up research using a more comprehensive data set.

4.1.3 Trade Openness

Our results point to a significantly positive long-run relationship between global trade openness and MFP, with an elasticity of 0.2. We use trade openness as a proxy for globalization, hoping that it would capture some of the effects of international competition, offshoring (international outsourcing), technological transfers via foreign direct investment and trade in technology services. By using one measure for all industries we are not capturing the heterogeneity of the implications of globalization for individual industries. Nonetheless, part of these effects might be captured by the outsourcing and markup factors. One advantage of using one common measure of globalization is better control of cross-sectional depen-

[32] At the aggregate level, outsourcing to efficient foreign suppliers could potentially boost domestic productivity by inducing more competition and reallocation of output from less to more productive firms or industries.

dence in error terms which could invalidate the pooled mean group estimator. Moreover, the global measure is more exogenous than the industry-specific ones as many studies found that self-selection based on productivity tends to drive entry into export markets.

4.1.4 Markup

Surprisingly, the coefficient on the markup measure is positive. On the face of it, our finding implies that in the long run, competition inhibits, rather than stimulates efficiency gains. It could be that, as Aghion et al. (2005) argue, competition in Canadian industries has evolved over time to a level too high or too low to induce a positive response of innovation to competition.[33] However, one needs to exercise caution in embracing this interpretation. Boone (2000) points out that markup may not be monotone in competition when firms differ in their marginal cost levels. The reallocation of output from firms with low markup (high marginal cost) to high markup (low marginal cost) as a result of competition could raise the industry markup under certain conditions. Another possibility is that increased innovation, captured by higher MFP, is leading to higher markups in the industry. For example, product innovations by a few firms in the industry may allow them capture a higher share of the industries output and charge higher prices at the same time. The cointegration based analysis by itself cannot shed any light on the direction of causality.

4.1.5 Short-Run Dynamics

With PMG, the lag orders of explanatory variables, short-run coefficients (including the speed of adjustment to disequilibrium) and error variances are all allowed to vary by cross-sectional unit. In our case, the results do suggest heterogeneity in the dynamics of MFP in response to various short-run changes across different industries. The speed of adjustment is -1 in two

[33] Note that the positive relationship between the markup and MFP is not due to the fact that MFP is constructed assuming perfect competition and constant returns to scale. It can be shown that when capital is growing faster than labour the price over marginal cost markup is negatively related to measured MFP (see Leung (2007)). Futhermore, deviations from returns to scale only affect the magnitude of relationship between the price over marginal cost markup and measured MFP and not the sign.

industries (Utilities and Construction) as there is no lagged dependent variable in the ARDL model for the two industries. The remaining industries with a negative and significant speed of adjustment are Retail Trade (-0.89), Manufacturing (-0.84), Information and Cultural Industries (-0.45), Transportation and Warehousing (-0.28), Finance, Real Estate, Rental and Leasing (-0.16). The average speed of adjustment to disequilibrium comes out to be -0.40 (significant at the 1% level), or about 40 percent a year. This means that about 95 percent of the deviations in MFP from its long-run equilibrium due to shocks to its determinants in a particular year should be corrected in 5 years, on average, if no new shock is received. The delay in the full response of MFP may indicate adjustment costs associated with learning curve, installation and setup, or organizational changes that often accompany investments in new technology and process, changes in "make-or-buy" decision or strategic shifts in the face of tough competition.

The coefficient on the utilization rate is positive on average, but not significant at the conventional level.[34] The average coefficients on the current and lagged (up to 2 years) growth rates of ICT are all negative, but insignificant. Only for manufacturing and retail trade is the sum of the short-run coefficients on ICT significantly negative, suggesting adjustment costs may be at play. The first lag of the change in outsourcing, the second lag of the change in markup, and the current year change in global trade openness also turn out to be negative and significant on average. These are mostly driven by the individual results for Manufacturing, Construction, Wholesale Trade, Retail Trade, Information and Cultural Industries.

4.2 *Mean Group and SUR Results*

The PMG approach imposes the homogeneity restriction on the long-run coefficients. While it can be argued that ICT as a common technology and globalization as a common trend may affect industries more or less the same way, it is less obvious why changes in outsourcing

[34] Using the change in the utilization rate does not affect the results significantly.

practices and competition should incur the same impact on MFP across industries. Relaxing the long-run homogeneity restriction results in the mean group (MG) estimator, which takes the simple average of the separate estimates for each group. To verify the validity of the homogeneity restriction, a Hausman-type test can be applied to the difference between the PMG and MG estimators. Under the null of long-run homogeneity, the PMG estimator is both consistent and efficient. Under the alternative, the MG estimator is better. The third and fourth columns in Table 5 show the long-run coefficient estimates using MG and the associated significance level of the Hausman test. It turns out that the MG estimates are insignificant. Their large standard errors lead to low power of the Hausman test. The coefficient on ICT of 0.003 is marginally higher than the one obtained by PMG. The speed of adjustment, at -1.08, is implausible. Considering that previous research has shown the MG estimator to perform poorly when either N or T is small (Hsiao et al. (1999)), we think that in our case the PMG results are more reliable.

Another key assumption of the PMG approach is that the errors are independently distributed across groups. However, in the real world macroeconomic shocks rarely affect individual industries in isolation. It is also possible that contemporaneous correlation of disturbances exists because of unobserved common trends among industries that have not been taken care of by the variables included in the model. While the Breusch-Pagan LM test based on the residuals from the PMG estimation shows no evidence of cross-sectional dependence among error terms, we still proceed to a Seemingly Unrelated Regression (SUR) estimation of the error-correction model. The specification remains exactly the same as under PMG, and all the long-run parameter restrictions are retained as well. The results (shown in the last column of Tables 5 and 6) indicate no major problem in assuming cross-sectional independence, as using SUR instead of PMG does not change the sign or significance of the long-run coefficients and the speed of adjustment. The short-run dynamics are affected a bit more, but the signs are mostly consistent with those using PMG. The impact of ICT and trade on MFP is greater with SUR, while that of outsourcing and markup is smaller. The industry average speed of adjustment is around 35 percent a year, somewhat lower than in the case of PMG. Utilization is still positive on average, but significant. Overall the difference between the estimates given by SUR and PMG is not so significant as to change our main conclusions.

4.3 *Contribution of Factors to MFP Growth*

The parameter estimates obtained from the ECM can be used to split the growth in MFP by industries into an error-correction component and other components due to short-run impacts from changes in the explanatory variables. Furthermore, assuming that the partial speed of adjustment of MFP to the deviation from the long-run "fundamental level" attributed to each factor is the same as the overall speed of adjustment (*phi*) and that at the beginning of the sample, the system was at equilibrium, one can decompose MFP growth into contributions by factor. The contribution of ICT each year, for example, would be calculated as the adjustment of MFP to ICT-induced disequilibrium plus the effect of current and lagged growth of ICT (see Equation 3). Note that the equal partial adjustment assumption is quite strong and therefore results obtained herein should be treated as suggestive in nature.

$$\Delta \ln(MFP_{i,t}^{ICT}) = \widehat{\phi}_i(\ln(MFP_{i,t-1}^{ICT}) - \widehat{\theta}\ln(ICT_{i,t})) + \sum_{j=0}^{q-1} \widehat{\delta}_{i,j}\Delta \ln(ICT_{i,t-j}) \tag{3}$$

Applying this decomposition exercise to the four industries that pass most of the diagnostic tests as outlined in the beginning of Section 5, one obtains the results shown in Table 7. Note that while data are available back to 1976, the earlier years are dropped as they are most affected by the starting value assumptions. Over the 1980 – 2003 period, MFP grew at an annual average rate of 0.62 percent in Retail Trade, 0.49 percent in Information and Cultural Industries, 0.38 percent in Manufacturing and 0.10 percent in Transportation and Warehousing. ICT contributed about a third of the MFP growth for Transportation and Warehousing, slightly more than a quarter of the growth for Manufacturing, and less than 18 percent of the Retail Trade MFP growth. The average contribution from ICT to Information and Cultural Industries was negative, reflecting a drag from slow growth in ICT capital accumulation before the mid-90s. The sign of ICT contribution changed between the late 90's and the opening years of the 21st century for all four industries in the table. For Manufacturing, Transportation and Warehousing, Information and Cultural Industries, ICT subtracted from MFP growth over the 1995 – 1999 period, but substantially enhanced it in later years. The opposite was true for Retail Trade. One explanation for this phenomenon relates to the adjustment cost theory which suggests that the productivity-enhancing benefits of ICT investment may be realized with a long delay as the new capital is installed, workers trained and organizational changes take place. Figure 1 shows the growth in ICT capital services by industry. Rapid acceleration in the accumulation of ICT capital in the late 1990s occurred for all industries except Retail Trade. The benefits of this investment wave were not realized until several years later (2000 – 2003) when ICT investment decelerated in most industries (which also brought down adjustment cost).

Global trade openness made positive contributions to the growth of MFP in all four industries post-1980, as did outsourcing. In addition, outsourcing was the key contributing factor overall for the three services industries. No dominating theme seems to emerge for Manufacturing – markup, globalization and ICT were important at one time or another.

5 Conclusions

Given the significant role MFP has played in driving the fluctuations in labour productivity growth in Canada over the past four decades, it is important to understand the determinants of MFP in the long-run. The literature provides us with a fairly long list of variables to consider, with recent interests centered around Information and Communications Technology (ICT). Panel studies in this area tend to focus on one or two determinants at a time, as it is difficult to compile time series data on many variables that are consistent along the cross-sectional dimensions. Even in the case of ICT alone, the empirical evidence of its impact on MFP at the industry level has been mixed and sensitive to the choice of lag structures in the typical growth accounting type of model. In addition, most ICT-related studies have been done for the U.S. where the history and magnitude of ICT investment have been well documented.

In this paper, we apply the Pooled Mean Group (PMG) estimator by Pesaran et al. to a dynamic heterogeneous panel of twelve Canadian industries in order to explore the long-run relationship between MFP and a number of variables including ICT, outsourcing, competition, trade openness, public infrastructure and R&D. The advantage of this particular estimator is that it allows the long-run elasticities to be efficiently estimated by pooling across industries while providing a means for testing this poolability. The speed of adjustment, the lag structure, the short-run elasticities, and the error variance are all allowed to vary by industry, thus providing a more realistic framework for modelling industry adjustments to deviations from the equilibrium. By focusing on the long-run relationship, the PMG approach effectively deals with the problem caused by the uncertain timing between the growth in MFP and changes in its determinants. It is also more robust to outliers than some other approaches that model each industry separately.

Our results suggest that ICT capital, outsourcing and global trade openness have a statistically significant positive effect on MFP. The long-run impact of ICT is quite small, but its contribution to recent MFP growth is found to be quite large for a number of industries, possibly reflecting the delayed benefits of the ICT investment surge in the late 1990s due to adjustment costs. More global trade openness and outsourcing generally raise MFP, likely due to cost reduction due to specialization, economies of scale, and technological spillover across industry and national borders.

An important limitation of this study is that the test of the restriction of long-run homogeneity may be of low power because of the relatively small sample size in the cross-sectional dimension. A more extensive data set comprising industries at the three-digit NAICS level would allow us to better determine whether the long-run relation between MFP and its determinants are indeed identical. It will also enable separate analysis for the goods and services sectors where outsourcing, for example, may play a differing role. In addition, more recent panel unit root and cointegration techniques accounting for unobserved common trends and other complex issues could be employed in a richer data set, thus providing better guidance in selecting the most appropriate modelling strategy.

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Appendix

1. Main Data Source

The majority of the data used in this paper were from Statistics Canada CANSIM Tables 383-0021 and 383-0022 released on June 25, 2007. The following industries were combined into "Other Services" mentioned throughout the text:

- Administrative and support, waste management and remediation services
- Arts, entertainment and recreation
- Accommodation and food services
- Other services, except public administration

To convert Y, K, L, U and MFP from index form to levels in terms of chained 2002 dollar, author's own calculations were used, as follows:

Step 1 Use the nominal values of 2002 as the chained values for the same year for Y, K, L and U.

Step 2 Apply the annual growth rates derived from the index form to the base values of 2002 to obtain the level of variables Y, K, L and U.

Step 3 To obtain the 2002 value of MFP in dollar terms, divide gross output by the weighted product of K, L and U, with weights being the 2-period average share of factor income.

Step 4 Apply the annual growth rates derived from the index form to the base 2002 value to obtain the historical levels of MFP in chained dollar terms.

2. Calculation of R&D Intensity and Stock by Industry

(A) **R&D intensity**

These estimates were derived from a number of different CANSIM Tables (282-0008, 379-0025, 358-0001, 358-0024, 379-0017).

Step 1 Employment shares were calculated using LFS estimates by industry for each province. For the provinces or industries for which this data was missing, industry splits were calculated using GDP shares.

Step 2 Multiplying the industry split ratios by the total business sector intramural R&D expenditures (1997 constant dollars) for each province generates a proxy of provincial R&D spending in each industry.

Step 3 These figures were then summed up across provinces resulting in an estimate of national business sector R&D expenditures for each industry.

Step 4 The growth rates of these calculated series were then applied to the 1997 levels of actual business enterprise R&D expenditures for each industry in order to project R&D expenditures as far back as possible.

Step 5 Finally, the projected R&D expenditures for each industry were divided by the respective industry GDP series, resulting in measures of R&D intensity for each industry in Canada over time.

(B) **Own R&D stock**

The real R&D expenditures obtained in Step 4 above were then used to derive industries' own R&D stock using a perpetual inventory method:

$$RD_t = (1 - \delta)RD_{t-1} + I_t \tag{4}$$

where RD_t is the end of period R&D capital stock and I_t is real R&D expenditure (i.e. investment). A depreciation rate (δ) of 10 percent is assumed.

The R&D capital stock at the beginning of the sample is defined as

$$RD_0 = I_0/(g + \delta) \tag{5}$$

where g is the average growth rate of real R&D spending during the entire sample period (1987 – 2003). Note that the magnitude of this parameter only affects the initial stock level.

(C) **R&D spillover effect**

In addition, each industry also receives spillover effects from other industry's R&D activities. We assume that if industry i uses industry j's output as intermediate input, then there exists a technology flow from j to i defined as

$$RD_j \cdot SOR_{j,i} \tag{6}$$

Table 1: Input-Output Ratios %

j	*11*	*21*	*22*	*23*	*3133*	*41*	*4445*	*4849*	*51*	*5253*	*54*	*5681*
i												
11		0.08	1.64	0.85	0.58	1.55	0.21	0.96	0.57	0.93	0.53	2.02
21	0.00		3.51	0.71	0.25	0.95	0.05	0.41	0.38	1.30	2.04	2.56
22	0.01	1.38		1.09	0.06	0.11	0.01	0.20	0.24	0.43	0.40	0.44
23	0.89	3.09	0.28		2.24	6.11	0.93	1.39	0.76	1.76	8.73	2.06
3133	38.21	17.86	19.40	1.55		12.69	0.36	7.08	4.16	6.49	9.47	11.88
41	0.14	0.09	1.78	0.20	0.18		0.17	0.95	5.55	3.56	3.85	2.82
4445	0.00	0.10	4.49	0.37	0.13	0.34		0.38	5.43	5.28	3.37	2.49
4849	0.01	0.09	1.52	1.88	0.47	1.43	0.22		3.22	1.59	1.40	2.99
51	0.00	0.02	0.56	0.58	0.27	0.26	0.12	0.16		1.19	1.73	2.50
5253	0.00	0.24	6.55	7.42	0.07	0.49	0.22	0.21	10.74		10.05	7.15
54	0.00	0.02	0.43	0.07	0.03	0.08	0.04	0.04	3.49	1.87		3.12
5681	1.12	0.06	3.21	0.40	3.37	9.30	5.35	7.16	11.95	4.15	7.79	

Note: Please refer to Section 4.1 for a description of the industries.

where $SOR_{j,i}$ is the proportion of nominal gross output of industry j used as intermediate input by industry i.[35] Table 1 gives the average SOR over the period 1987 – 2003 by industry. Summing (8) over j, where $j \neq i$, we obtain the overall spilled-over R&D expenditure received by industry i. This can then be cumulated into a stock measure (SRD_i) in the same way as own R&D stock is calculated

3. Other Tables and Graphs

[35] Calculated from the 2003 Input-Output tables at the S-level of aggregation (CANSIM Table 381-0013).

Table 2: Average Annual Growth Rates of Selected Variables (Percent)

	MFP	ICT	Outsource	Markup1	Markup2	Trade Openness	Public Infrastructure	Mass Infrastructure	R&D Intensity	R&D Stock	R&D Spill-Over
Agriculture, Forestry, Fishing and Hunting	0.72	18.71	0.78	-0.74	0.45	0.58	0.50	0.75	0.64	0.95	7.21
Mining and Oil and Gas Extraction	-1.22	17.53	0.29	-1.17	-0.55	0.58	0.50	0.75	-0.35	-0.04	8.28
Utilities	0.45	23.09	0.23	0.02	1.06	0.58	0.50	0.75	2.45	2.70	10.69
Construction	0.27	27.32	0.15	0.04	0.13	0.58	0.50	0.75	0.27	2.42	5.93
Manufacturing	0.50	21.63	0.07	0.14	0.18	0.58	0.50	0.75	6.63	2.09	7.42
Wholesale Trade	1.18	21.80	0.46	0.00	-0.01	0.58	0.50	0.75	1.50	3.71	10.20
Retail Trade	0.63	20.58	0.34	-0.05	-0.01	0.58	0.50	0.75	0.20	2.82	6.69
Transportation and Warehousing	0.37	21.38	0.22	0.03	-0.40	0.58	0.50	0.75	0.12	3.07	5.38
Information and Cultural Industries	0.89	7.30	0.60	-0.74	0.13	0.58	0.50	0.75	0.62	3.75	11.80
FIREL	-0.31	21.67	0.38	-0.60	0.11	0.58	0.50	0.75	0.13	2.78	5.78
Professional, Scientific and Technical Services	-1.40	24.71	0.59	-0.33	0.00	0.58	0.50	0.75	7.16	6.50	8.75
Other Services (except Public Administration)	-1.25	22.52	0.17	-0.14	0.02	0.58	0.50	0.75	0.95	3.86	8.41

Notes:
(1) All numbers are averaged over 1977 -- 2003, except R&D measures which are averages over 1988 -- 2003.
(2) For ratio variables (outsource, markup, globalization, R&D intensity), growth rates are calculated as the difference in annual values. For all other variables, growth rates are the first difference in logs.

Table 3: Unit Root Tests, 12 Industries

Variable	IPS	Hadri_1	Hadri_2	Hadri_3	CADF	ADF	PP
ln(*MFP*)	-2.301	22.028***	20.388***	7.316***	-2.130		
	(0.206)	(0.000)	(0.000)	(0.000)	(0.760)		
ln(*ICT*)	-1.837	33.662***	30.878***	11.828***	-2.363		
	(0.848)	(0.000)	(0.000)	(0.000)	(0.436)		
outsource	-2.299	21.765***	20.408***	8.252***	-2.586		
	(0.208)	(0.000)	(0.000)	(0.000)	(0.161)		
markup1	-2.399	24.774***	12.349***	9.847***	-2.653		
	(0.113)	(0.000)	(0.000)	(0.000)	(0.107)		
markup2	-2.314	26.689***	23.519***	9.991***	-1.729		
	(0.192)	(0.000)	(0.000)	(0.000)	(0.986)		
RDI	-2.455*	6.990***	2.658***	4.537***	-1.450		
	(0.066)	(0.000)	(0.004)	(0.000)	(0.998)		
RD	-1.736	23.532***	21.143***	8.769***	-2.316		
	(0.875)	(0.000)	(0.000)	(0.000)	(0.450)		
SRD	-1.802	23.727***	23.642***	8.192***	-1.928		
	(0.817)	(0.000)	(0.000)	(0.000)	(0.889)		
ln*(infra_g)*						-0.849	-0.682
						(0.961)	(0.974)
ln*(infra_m)*						-1.978	-2.689
						(0.614)	(0.241)
trade openness						-0.943	-1.185
						(0.951)	(0.913)

Notes:

(1) Tests applied to the 1976 -- 2003 sample, except for R&D variables which are available for 1987 -- 2003.

(2) *p* values in brackets. * significant at 10% level, ** 5%, *** 1%.

(3) IPS is the Im-Pesaran-Shin (2003) panel unit root test on cross-sectionally demeaned panel data to eliminate common time effects. A constant, individual time trend and a maximum of 2 lags of the dependent variable are included.

(4) Hadri refers to the Hadri (2000) test of stationarity on panel data. Hadri_1: homoskedastic disturbances across units; Hadri_2: heteroskedastic disturbances across units; Hadri_3: serial dependence in errors.

(5) CADF is the Pesaran (2003) panel unit root test in the presence of cross sectional dependence. A time trend and a lag truncation of 2 are used.

(6) ADF and PP are the Augmented Dickey-Fuller and Phillips-Perron unit root tests applied to individual time series. These tests incorporate a maximum of 2 lags and a time trend. They are used for variables that don't vary across industries.

Table 4: Pedroni's (1999) Cointegration Tests, 1976 - 2003, 12 Industries

	No Trend	With Industry Specific Trend
Panel *v* -statistic	0.505	0.016
Panel *rho*- statistic	0.614	1.412
Panel *PP* -statistic	-1.735**	-1.849**
Panel ADF-statistic	-2.466***	-2.262**
Group *rho* -statistic	1.862	2.461
Group *PP* -statistic	-1.354*	-1.794**
Group ADF-statistic	-2.217**	-1.772**

Notes:
(1) Variables included are ln(*MFP*), ln(*ICT*), *outsource*, *markup1* and *trade openness*.
(2) All reported values are distributed $N(0,1)$ under the null of no cointegration. The panel *v*-statistic requires a value greater than 1.64 for the rejection of the null at the 5% level, while the others require a value less than - 1.64.
(3) * significant at 10% level, ** significant at 5% level, *** significant at 1% level.
(4) The maximum of lags in the ADF based tests is 3.

Table 5: ECM Results, Long-Run

Dependent Variable: dln(*MFP*) -- Growth Rate of Industry *MFP* Based on Gross Output

	Pooled Mean Group (PMG)	Mean Group (MG)	*p*- val of Hausman Test	Seemingly Unrelated Regression (SUR)
Long-Run Coefficients				
ln(*ICT*)	0.002*	0.003	0.99	0.005***
	(0.002)	(0.017)		(0.001)
outsource	0.810***	0.686	0.86	0.476***
	(0.127)	(0.721)		(0.089)
markup1	0.674***	0.241	0.33	0.086***
	(0.074)	(0.453)		(0.021)
trade openness	0.213***	-0.443	0.06	0.320***
	(0.050)	(0.355)		(0.044)
Joint Hausman Test of Long-Run Homogeneity			0.31	

Notes:
(1) d denotes first difference, ln denotes natural log, and dln denotes difference in ln.
(2) All equations include an industry -specific constant term and lagged first difference of long-run variables with the lag order selected by Schwarz Information Criteria up to a maximum of 3.
(3) Standard errors in brackets.
(4) * significant at 10% level, ** significant at 5% level, *** significant at 1% level.
(5) Short-run coeffients reported here are averages of unrestricted MG estimates of industry specific coefficients under the restriction of long-run homogeneity.
(6) Joint Hausman test statistic is indeterminate if the difference between the variance-covariance matrices of the PMG and the MG estimators is not positive definite, noted as "N/A".

Table 6: ECM Results, Short-Run

Dependent Variable: dln(*MFP*) -- Growth Rate of Industry *MFP* Based on Gross Output

	Pooled Mean Group (PMG)	Mean Group (MG)	Seemingly Unrelated Regression (SUR)
Short-Run Coefficients			
phi : Speed of Adjustment	-0.399***	-1.077***	-0.352***
	(0.121)	(0.213)	(0.021)
urate	0.588	0.613**	0.270***
	(0.499)	(0.275)	(0.075)
constant	-0.763*	-0.478	-0.126*
	(0.538)	(0.418)	(0.068)
dln(*MFP*)[t-1]	0.014	0.165	-0.012
	(0.076)	(0.163)	(0.060)
dln(*MFP*)[t-2]	0.061	0.156*	0.119*
	(0.070)	(0.105)	(0.067)
dln(*ICT*)	-0.005	0.006	-0.000
	(0.010)	(0.031)	(0.011)
dln(*ICT*)[t-1]	-0.008	-0.026**	-0.032**
	(0.019)	(0.016)	(0.014)
dln(*ICT*)[t-2]	-0.001	-0.001	-0.008
	(0.013)	(0.016)	(0.031)
d(*outsource*)	0.042	-0.121	-0.366**
	(0.179)	(0.383)	(0.171)
d(*outsource*)[t-1]	-0.187**	-0.139	-0.710***
	(0.097)	(0.319)	(0.164)
d(*outsource*)[t-2]	-0.139	-0.075	-0.515***
	(0.114)	(0.257)	(0.198)
d(*markup1*)	0.085	-0.391	0.250*
	(0.114)	(0.423)	(0.051)
d(*markup1*)[t-1]	0.035	-0.129	-0.012
	(0.094)	(0.280)	(0.085)
d(*markup1*)[t-2]	-0.121*	-0.111	-0.155
	(0.081)	(0.178)	(0.097)
d(*trade*)	-0.143***	0.182	-0.138*
	(0.061)	(0.193)	(0.078)
d(*trade*)[t-1]	-0.019	0.042	-0.184**
	(0.087)	(0.141)	(0.080)
d(*trade*)[t-2]	-0.026	0.051	0.018
	(0.040)	(0.079)	(0.075)
Number of Industries	12		
Number of Years	28		
Log Likelihood	859.6		

Notes: See notes for Table 6.

Table 7: Contribution to MFP Growth -- Selected Industries

	1980 - 2003	1980 - 1994	1995 - 1999	2000 - 2003
	Percentage			
Manufacturing				
MFP	0.376	0.343	0.556	0.278
ICT	0.107	0.153	-0.293	0.438
outsource	0.022	-0.073	0.270	0.066
markup1	0.175	0.213	0.307	-0.134
trade	0.105	0.040	0.289	0.120
urate	0.065	0.083	0.058	0.004
residual	-0.097	-0.072	-0.075	-0.217
Retail Trade				
MFP	0.621	0.146	1.492	1.313
ICT	0.110	0.066	0.520	-0.241
outsource	0.252	0.217	0.368	0.239
markup1	0.011	-0.188	0.182	0.544
trade	0.106	0.052	0.271	0.100
urate	0.245	0.278	0.329	0.014
residual	-0.103	-0.280	-0.179	0.657
Transportation and Warehousing				
MFP	0.102	0.289	-0.600	0.278
ICT	0.034	0.008	-0.269	0.514
outsource	0.181	0.227	0.108	0.097
markup1	0.024	0.012	0.110	-0.037
trade	0.049	-0.037	0.052	0.370
urate	-2.073	-3.173	-0.267	-0.205
residual	1.886	3.252	-0.333	-0.460
Information and Cultural Industries				
MFP	0.489	0.431	0.125	1.164
ICT	-0.091	-0.153	-0.166	0.232
outsource	0.535	0.431	0.687	0.736
markup1	-0.601	-0.324	-1.628	-0.358
trade	0.096	0.004	0.114	0.416
urate	6.675	10.044	1.405	0.626
residual	-6.124	-9.572	-0.287	-0.488

Figure 1: Growth in ICT Capital Services