Towards a Theory of TFP*

Carlaw, K. I.[1] and R. G. Lipsey[2]
[1]University of Canterbury and University of British Columbia, [2]Simon Fraser University, E-Mail: kenneth.carlaw@canterbury.ac.nz

Keywords: *Economic Growth; Productivity; Technological Change*

EXTENDED ABSTRACT

We begin the development of a theory of total factor productivity (TFP) by presenting a multi-sector model of general purpose technology (GPT) driven growth, which generates numerical data via simulation and confirm the theoretical predictions of Carlaw and Lipsey (2003) and Lispey and Carlaw (2004) that TFP is not a contemporaneous measure of technological change. The modeling framework enables comparison between simulated rates of technological change and measures of TFP growth calculated from the simulated data. Theoretical assumptions such as returns to scale and returns to knowledge in the production function and there effect on the TFP calculations can be tested. It is demonstrated that in cases where the generation and adoption of new technology has resource costs that are capitalized in the TFP growth calculation, TFP growth does not measure the introduction of a new GPT. Furthermore, under assumptions that the introduction of new transforming GPTs requires investment in structural adjustment, TFP growth slows while the technology diffusion rate increases and then increases while the diffusion rate declines generating a negative contemporaneous correlation between the two. Our theoretical findings are compared with the growth experience of a number of OECD economies with special focus on Australia's and New Zealand's experiences with ICT. TFP growth and ICT diffusion rates are calculated and compared to check the robustness of the modeling framework. Preliminary results yield limited evidence that is consistent with the model's prediction that as a transforming new GPT such as ICT enters the economy TFP growth will slow and stay low while diffusion rates increase, then TFP growth increases as the technology matures. The results refute the implicit empirical hypothesis of endogenous and exogenous growth theory that TFP growth is a positive contemporaneous measure of technological change.

* The authors gratefully acknowledge funding support for this research from the Royal Society of New Zealand's Marsden Fund grant number UOC101 and consultancy contracts with the Australian National Office for the Information Economy and the Department of Communications, Information Technology and the Arts.

1. INTRODUCTION

This paper is about the interpretation of TFP which has been associated with economic growth or lack thereof caused by information and communication technology (ICT). We separate the diffusion of ICT from measured output or productivity gains generated by it in order to determine the causes of TFP and wider economic growth.

There is little disagreement that computers, the Internet and the myriad supporting complementary technologies that they have enabled, have revolutionized production taking the world into the age of the global economy.[1] What is debated is whether this technological revolution is having the kinds of revolutionary influences on economic growth that were witnessed with the First and Second Industrial Revolutions. At the centre of a current debate on long-run productivity growth is the so called productivity paradox. The erroneous presumption that underwrites the paradox is that TFP measures technological change.

We develop a theory consistent with David (1990), David and Wright (1999), the theoretical models in Helpman (1998) and Lipsey, Bekar and Carlaw (1998) who argue that there is no paradox because of the existence of a real technology cycle. We argue that the introduction of new GPTs can cause large structural adjustment costs as the economy exploits the new technology.

2. TECHNOLOGICAL CHANGE AND TFP

Measures of TFP change are often interpreted to be the rate of technological progress within an economy. This requires a definition of technology in terms of output and its associated inputs. Technology is not defined and measured independent of economic performance. In this view the measurement of technological change does not require observations that are independent of output. Nor is it necessary to develop a theory that explains how technology leads to economic growth because the two are conceptually inseparable.

A number of economists that study productivity, economic history, technological change and economic growth have argued that TFP is not a measure of technological change. Technological change is recognized as endogenous to economic choices and bears the cost of the resources used to embody the technology, costs which are capitalized in the inputs of the TFP calculation. Technology is independent of the traditional aggregate outputs and inputs measures.

There are two ways to demonstrate that TFP change is not a measure of technological change. First, endogenous technological change is brought about by the allocation of resources that have opportunity costs to the activity that generates the new technology. Second, measures of technological change, which are independent of measures of economic performance, show a negative correlation with the pattern of TFP change.

Virtually all technological change becomes embodied in one form or another: new or improved products, capital goods or other forms of production technologies, and new forms of organization in finance, management or on the shop floor. Almost all of technological change results from resource-using activities and the costs involved in creating such change are more than just conventional R&D costs. They include costs of installation, acquisition of tacit knowledge, learning by doing in making the product, and learning by using it, plus a return on the entrepreneurial investment of funds in development costs. Lipsey and Carlaw (2004) refer to the sum of these as "development costs"[2] and illustrate the point with a simple algebraic analysis.

The contributions of embodied technological change to TFP growth have been studied in the growth accounting literature. Hulten (1992) and Jorgenson (1966) argue that quality change (or Investment Specific Technological (IST) change growth) is difficult to observe, and therefore may not be measured accurately in the National Income and Product Accounts (NIPA).

An analysis of change in investment quality and TFPG for 16 OECD countries where comparable data was available reveals a negative relationship between ISTC and TFPG for most of the countries. The data span the period 1970 to 1997, although the time series are shorter for some of the countries included

[1] However, some economist, such as, Young (1992) and Krugman (1996) commenting on Young argue that the lack of high total factor productivity in the Asian economies that experience exceptional growth in GDP per capita throught the 1970s and 1980s is evidence that no technological revolution occurred in these economies.

[2] Jorgenson and Griliches (1967) argued that changes in TFP would only measure the gains in output that were over and above the development costs of the technological advance that caused the gains.

in the analysis. Correlations and their significance are calculated by linearly regressing TFPG on ISTC. (See Table 4.1 below.)[3]

3. MODELS OF GPT-DRIVEN GROWTH

Our model has the following key characteristics. GPTs arrive at randomly determined times with an impact on the productivity of applied R&D that is determined by the amount of pure research knowledge, which has been endogenously generated since the last GPT and elements of randomness. The sources of randomness defined above imply that short term outcomes are influenced by the particular realizations of the random variables, allowing the average growth rate of output over the lifetime of each successive GPT to differ from that of its predecessor. However, the average growth rate over long periods of time in which several GPTs succeed each other is determined by the accumulated amount of pure knowledge. This is partly endogenous (determined by the allocation of resources to pure research), and partly exogenous (determined by random factors affecting the productivity and timing of those resources). Furthermore, while some GPT driven research programs are richer than others, successive GPTs will not always either accelerate or decelerate growth on average over their lifetimes. There is no expectation that each new GPT will produce a productivity bonus in the form of acceleration in productivity growth.

There is a generic input called resources, R_t, allocated among the various consumption sectors, $r^j_{c,t}$, applied R&D sectors, $r^j_{a,t}$, pure knowledge sectors $r^x_{g,t}$ and structural adjustment sectors, $r^x_{s,t}$. There are J of the consumption and applied Sectors and X of the pure knowledge and structural adjustment sectors.

(1) $$R_t = \sum_{j=1}^{J} r^j_{c,t} + \sum_{j=1}^{J} r^j_{a,t} + \sum_{x=1}^{X} r^x_{g,t} + \sum_{x=1}^{X} r^x_{s,t}\ .$$

The flow of consumption output in each of the j lines of consumption, $c_{j,t}$ in (2) is a function of the resources allocated to the consumption sector, $r_{c,t}$, and the productivity coefficient μA_{t-1}.[4] The parameter μ is used to apportion the stock of applied knowledge between consumption and pure knowledge production.

(2) $$c_{j,t} = (\mu A_{j,t})^{\alpha_1} (r^j_{c,t})^{\alpha_2}, \quad \text{with } \alpha_i \in (0,1],\ \ i = 1,2 \text{ and } \alpha_2 < 1.$$

Applied R&D utilizes GPTs produced from each of the X pure knowledge sectors so the production function for each applied R&D activity has X + 1 arguments, X types of GPT knowledge, and resource inputs. The model captures the behaviour of GPTs acting as complements and as a displacer of the GPT that exists from the same line of pure knowledge research. Whether the new GPT is chosen depends on whether the set of GPTs and their related ν^x_j and κ^x_j parameters (defined in equation 3 below) create the most output with the new GPT or the old GPT. In either case the choice between the first two terms is then complementary with the resources allocated to each line of applied R&D. Each line of production of applied knowledge is altered to include the possibility of allocating resources to the activity of adjusting the structure with a structural adjustment cost, SA_t, defined in (8), which reduces the immediate impact of the new GPT on productivity in that particular applied R&D sector.

(3)
$$a_{j,t} = \max \left\{ \begin{array}{l} \left[\prod_{x=1}^{X} \left(\nu^x_{j,t^x_z} \chi G_{x,t_z} (\kappa^x_{j,t_z} SA_{x,t_z})^{\beta_{X+x}} \right)^{\beta_x} \right], \\ \left[\prod_{x=1}^{X} \left(\nu^x_{j,t^x_{z-1}} \chi G_{x,t_{z-1}} (\kappa^x_{j,t_{z-1}} SA_{x,t_{z-1}})^{\beta_{X+x}} \right)^{\beta_x} \right] \end{array} \right\} (r^j_{a,t})^{\beta_{2X+1}}$$

$$A_{j,t} = a_{j,t} + (1-\varepsilon) A_{j,t-1}$$

$$\beta_i \in (0,1), i = (1, \text{K}\ , X+1)$$

with $\beta_i \in (0,1],\ \ i = 1, \ldots, 2X+1,$

$$\nu^x_{j,t^x_z} \in V_t = \begin{cases} 0 \text{ with Prob } 0.5 \\ \text{Beta}(\text{x}|\nu,\eta) \text{ with Prob } 0.5 \end{cases}$$

and $\kappa^x_{j,t} \in K_t = \begin{cases} 0 \text{ with Prob } 0.5 \\ \text{Beta}(\text{x}|\nu,\eta) \text{ with Prob } 0.5 \end{cases}$

The random coefficients used to model the productivity of each of the X GPTs in the J lines of applied R&D, V_t, is an XxJ array of random variables with elements ν^x_{j,t_z}. The random coefficients for the effect of the structural adjustment costs from each GPT on

[3] Carlaw and Kosempel (2004) also demonstrate that IST is negatively correlated with TFP particularly since 1974.

[4] We subsequently simplify the model by not lagging the stock of applied R&D in the production function for consumption.

each line of applied R&D, K_t, is an XxJ array of random variables with elements $\kappa^x_{j,t}$.[5]

We model the productivity in each line of applied research as being determined by two forces: the first arrives as the productivity enhancing effect of the logistic diffusion of a the current x^{th} GPT ($\chi G_{x,t}$ in (3)) and the second is the effective structural adjustment cost associated with the x^{th} GPT ($SA_{x,t}$ in (3)). The effective structural adjustment depends on two things (see (8)), first, the accumulated amount of adjustment achieved by allocating resources to structural adjustment, which increases effective adjustment and, second, required further adjustment introduced by the arrival of a new GPT, which decreases current effective adjustment.

Resources are allocated among X types of pure knowledge research. GPTs arrive in each line of activity when $\lambda_{x,t} \geq \lambda^*_{x,t}$.

(4) $$g_{x,t} = \prod_{j=1}^{J} \left(\mu_j A_{j,t}\right)^{\sigma_j} \left(\theta_t r^x_{g,t}\right)^{\sigma_{J+1}},$$

$$\sigma_i \in (0,1], \quad i = 1,...,J+1.$$

Potential useful knowledge in each of the X lines of pure research is accumulated according to:

(5) $$G^p_{x,t} = g_{x,t} + (1-\delta) G^p_{x,t-1}$$

Actually useful pure knowledge (when the GPT arrives):

(6)

$$G_{x,t} = \varpi_{x,t_z} G_{x,t_{z-1}} + \left(\frac{e^{\tau+\gamma(t-t_{z,x})}}{1+e^{\tau+\gamma(t-t_{z,x})}}\right)\left(G^h_{x,t} - G_{x,t_{z-1}}\right)$$

where

(7)

$$G^h_{x,t} = \begin{cases} G^h_{x,t-1} + \vartheta\left(G^p_{x,t} - G^h_{x,t-1}\right) & \text{if } \lambda \geq \lambda^* \\ G^h_{x,t-1} & \text{otherwise} \end{cases}$$ and

$t_{z,x}$ is the arrival date of the z^{th} GPT in pure knowledge sector x, and γ and τ are control the rate of diffusion. θ_t is distributed uniformly with support [0.8, 1.2] and λ and ϑ are drawn from Beta distributions. (See Lipsey, Carlaw and Bekar (2005, Ch. 14)).

$SA_{x,t}$ is defined as follows:

(8) $$SA_{x,t} = \frac{S_{x,t}}{SC_{x,t}}.$$

The total amount of structural adjustment produced for the x^{th} GPT is determined by the relative productivity of resources in the x^{th} line of structural adjustment activity. These are highly productive when the GPT first arrives, then the resources migrate back out of the x^{th} line of activity in the structural adjustment sector as they become more productive elsewhere.

$SC^h_{x,t}$ holds the total cost of structural adjustment defined as a function of the total impact of the new x^{th} GPT, which we model by taking the difference between the total value of the new x^{th} GPT relative to the old and a random variable, $\psi_{x,t}$, drawn from a Beta distribution, defined in (12).

(9) $$SC^h_{x,t} = \psi_{x,t}\left(G^h_{x,t} - G^h_{x,t-1}\right).$$

The actual structural adjustment costs per period associated with the x^{th} GPT are assumed to follow a logistic diffusion process similar to the x^{th} GPT itself. The larger the GPT impact, the greater the structural adjustment that is required. We assume that $\gamma^x_s > \gamma^x, \tau^x_s < \tau^x$.

(10)

$$SC_{x,t} = SC_{x,t^x_z-1} + \left(\frac{e^{\tau^x_s+\gamma^x_s(t-t^x_z)}}{1+e^{\tau^x_s+\gamma^x_s(t-t^x_z)}}\right)\left(SC^h_{x,t} - SC_{x,t^x_z-1}\right)$$

The required structural adjustment, $S_{x,t}$, accumulates from the point that the x^{th} GPT arrives:

(11) $$S_{x,t} = s_{x,t} + S_{x,t-1}(1-\phi_{x,t}),$$

where

$$s_{x,t} = \left((1-\chi)G_{x,t}\right) r^x_{s,t},$$

and $$\phi_{x,t} = \begin{cases} \varsigma_{x,t} & \text{if } \lambda \geq \lambda^* \\ 0 & \text{otherwise} \end{cases},$$

The flow of structural adjustment, $s_{x,t}$, depends on the resources devoted to producing adjustment, $r^x_{s,t}$, and a portion of the stock of useful pure knowledge from the x^{th} line of pure research, $(1 - \chi) G_{x,t}$.

The random variable $\psi_{x,t}$ that conditions SC^h influences the total amount of new investment in structure required for the x^{th} GPT. The random variable, $\phi_{x,t}$, makes obsolete that portion of past investment in structure, $S_{x,t}$, which is not useful to the new GPT.

[5] Note that equation (3) represents the impact of the actual current stock of pure knowledge on the applied R&D sector where expectations of the current stock of pure knowledge are employed in the maximization procedure defined below.

$$\psi_{x,t} = o_x \left[\text{Beta}(x \mid \nu, \eta)\right], \quad 0 < o_x < 2 \tag{12}$$

The constant o_x allows the random variable drawn from the Beta distribution to take on values larger than one. This, combined with the calibration of ν and η, determines the probability that $\psi_{x,t}$ is greater than or less than one. $\varsigma_{x,t}$ is drawn from a uniform distribution with support of [0, 1].

The maximization problem includes the allocation of resources to J lines of final consumption, J lines of applied R&D, X lines of pure research and X lines of structural adjustment. Once again a representative agent with an additive utility function defined over the J lines of consumption output is assumed.

$$\begin{aligned}
&\max_{\{r^j_{c,t}, r^j_{a,t}, r^x_{g,t}, r^x_{s,t}\}} U(c^J_t) = \sum_{j=1}^{J} \left(c_{j,t}\right)^{\varphi_j} \\
&s.t. \\
&R_t = \sum_{j=1}^{J} r^j_{c,t} + \sum_{j=1}^{J} r^j_{a,t} + \sum_{x=1}^{X} r^x_{g,t} + \sum_{x=1}^{X} r^x_{s,t} \\
&c_{j,t} = (A_{j,t})^{\alpha_1} (r^j_{c,t})^{\alpha_2} \\
&a_{j,t} = \max \left\{ \left[\prod_{x=1}^{X} \left(\nu^x_{j,t^x_z} \chi G_{x,t} (\kappa^x_{j,t} SA_{x,t})^{\beta_{X+x}} \right)^{\beta_x} \right], \left[\sum_{x=1}^{X} \left(\nu^x_{j,t^x_z} \chi G_{x,t} (\kappa^x_{j,t} SA_{x,t})^{\beta_{X+x}} \right)^{\beta_x} \right] \right\} (r^j_{a,t})^{\beta_{2X+1}} \\
&A_{j,t} = a_{j,t} + (1-\varepsilon) A_{j,t-1} \\
&\bar{G}_{x,t} = \bar{g}_{x,t} + (1-\delta) G_{x,t-1} \\
&\bar{g}_{x,t} = \left(\mu A_{1,t}\right)^{\sigma_1} \left(\mu A_{2,t}\right)^{\sigma_2} \left(r^x_{g,t}\right)^{\sigma_3}
\end{aligned} \tag{13}$$

and equations (10 – 14)

Resources are allocated to maximise the utility from each line of consumption output in each current period by equating the expected marginal increase in consumption from a unit of resources allocated to each of the J applied R&D, X pure knowledge and X structural adjustment sectors of the model, but with productivity in each taken as given.

4. SIMULATION AND EMPIRICAL RESULTS

The model is solved using numerical simulation which requires calibrating parameter values. We choose values in order to achieve long run average growth rates of approximately 2% and GPT arrival rates of on average 30-35 periods. The qualitative results are robust to a wide rage of parameter values that meet the restrictions specified in the model. The growth properties of this model are discussed at length in Carlaw and Lipsey (2001, 2006 forthcoming) and in Lipsey, Carlaw and Bekar (2005 forthcoming, Chapter 14). Do to lack of space we do not report the calibration of the model for the simulations reported here.[6]

For the simulations we calculate TFP growth using a Tornquist index employing data defined by an accounting identity defined over all outputs and inputs in the system for the given simulation. We also calculate the rate of technological change directly from the simulation model. In all cases TFP underestimates the rate of technological change in the system. In cases where structural adjustment costs associated with the introduction of GPTs are included there is a negative contemporaneous correlation between TFP growth and the rate of technological diffusion. In all cases positive TFP growth is an indication of increasing returns to scale in the production system. When there are constant returns to scale TFP growth is zero and when there are decreasing returns to scale TFP growth is negative. In all cases technological change can be positive.

4.1 EMPIRICAL EVIDENCE AND CONCLUSIONS

The available empirical evidence for New Zealand and Australia, as well as a selection of 16 OECD economics for which comparable data is available, supports the theoretical findings of the pervious section. The test reported in this section are in no way meant to represent a complete test of the above theory of GPT driven growth, but they do are consistent with an implied empirical hypothesis in that theory and refute the implied empirical hypothesis of the only competing theory, namely neoclassical growth theory (either endogenous or exogenous). In the neoclassical theory TFP must be positively contemporaneously correlated with technological change (whether it is exogenous or endogenous). In our theory no necessary relationship exists in general and in cases where there are positive structural adjustment costs associated with the introduction of a new

[6] See Carlaw and Lipsey (2001), Carlaw (2004), Carlaw and Lipsey (2005), Lipsey, Carlaw and Bekar (2005) and Carlaw and Lipsey (2006 forthcoming) for various calibratins.

GPT there is an explicit negative contemporaneous relationship.

In the New Zealand and OECD data investment specific technological change is calculated as an independent measure of technological change and compared with measures of TFP. We report here some of our analysis of changes in investment quality and changes in TFP in sixteen OECD countries (where comparable data on national accounts, labour and productivity was available from the OECD) reveals that the negative relationship between IST and TFP change appeared in most of the countries in the data set. The data span the period 1970 to 1997, although the times series are not as long for some countries included in the analysis. Correlations and their significance are calculated by linearly regressing TFP growth on IST growth. This simple procedure allows for easy calculation of correlation and the statistical significance of the correlation between the two rates of change, however, it also has some obviously flawed assumptions. For example, it is unlikely that the relationship between TFP and IST growth is linear. We use it because reveals that there is clearly something wrong with TFP as a contemporaneous measure of technological change. We report these results in Table 4.1at the end of the paper. The results shown in Table 4.1 indicate that the relationship between MFP and IST is week. In most cases there is a negative relationship, in two cases a significant one.

Table 4.2 reports the same calculation, this time for 9 industrial sectors in New Zealand. Again a negative relationship seems to prevail however significance is greatly reduced perhaps due to the limited time serries of only 10 years (1989-99). However, when checked against the only other independent source of data on ICT diffusion in New Zealand, cellular telephone diffusion, the relationship between IST in the 9 industrial sectors and cell phone diffusion was prevailingly positive and in some cases significant.

In the Australian Data ICT diffusion rates are calculated from the available data on the productive contribution to the capital stock of computers and software.[7] A similar correlation calculation was made for 13 industrial sectors in Australia. These results are reported in Table 4.3. Again the negative contemporaneous relationship between TFP and technological change is supported by these data.

[7] This is only a partial measure of ICT diffusion as it does not include Internet, Broadband, etc.

REFERENCES

Carlaw, K. I. and R. G. Lipsey (2006 forthcoming) "GPT-Driven, Endogenous Growth", *The Economic Journal*.

Carlaw, K. I. and S. Kosempel (2004) "The sources of total factor productivity growth: Evidence from Canadian data" *Economics of Innovation and New Technology*, 13(4), 299-309.

Carlaw, Kenneth I. and R. G. Lipsey (2003) "Productivity, Technology and Economic Growth: What is the relationship?" *Journal of Economic Surveys*, 17(3).

Carlaw, Kenneth I. and Richard G. Lipsey (2001), 'Externalities versus Technological Complementarities: a model of GPT-driven, sustained growth', A Paper Presented at The Conference in Honour of the 20th Anniversary of Nelson and Winter's Book *An Evolutionary Theory Of Economic Change*, Aalborg Denmark, 12-15 June 2001.

David, P. and G. Wright (1999) "General Purpose Technologies and Surges in Productivity: Historical Reflections on the Future of the ICT Revolution", *University of Oxford Discussion s in Economic and Social History*, Number 31.

David. P. (1990) "The Dynamo and the Computer: An Historical Perspective on the Modern Productivity Paradox" *American Economic Review*, 80(2), 355-61.

Gordon, R.J., (2000) "Does the 'New Economy' Measure up to the Great Inventions of the Past?," *Journal of Economic Perspectives*, 14(4), 49-74.

Helpman, Elhanan, (ed) (1998) *General Purpose Technologies and Economic Growth*, (Cambridge: MIT Press).

Hulten, C. R. (1992). "Growth Accounting when Technological Change is Embodied in Capital," *American Economic Review*, 82(4), 964-980.

Jorgenson, D.W. (1966). "The Embodiment Hypothesis," *Journal of Political Economy*, 74(1), 1-17.

Krugman, Paul (1996) 'The Myth of Asia's Miracle,' in *Pop Internationalism* (Cambridge: MIT Press).

Lipsey, R. G., C. Bekar and K. I. Carlaw (1988) 'The Consequences of Changes in GPTs,' Chapter 7 in Helpman (1998).

Lipsey, R. G., K. I. Carlaw, and C. Bekar, (2005 forthcoming) *Economic Transformations: General Purpose Technologies and Long Term Economic Growth*, (Oxford, UK: Oxford University Press).

Lipsey, R. G. and K. I. Carlaw (2004) "Total Factor Productivity and the Measurement of Technological Change", *Canadian Journal of Economics* 37(4), 1118-50.

Young, A. (1992) 'A Tale of Two Cities: Factor Accumulation and Technical Change in Hong Kong and Singapore,' *NBER Macroeconomic Annual*, (Cambridge: MIT press).

TABLES

TABLE 4.1

	Correlation	(t statistic)	Ave. TFP growth	Ave. IST growth
Australia	-0.20	-1.63	0.57%	3.06%
Austria	0.08	0.80	1.62%	1.46%
Canada	-0.04	-0.45	0.49%	6.69%
Germany	-0.90	-1.91	0.24%	1.00%
Denmark	0.06	0.49	0.66%	1.37%
Spain	-0.17	-1.19	0.70%	1.75%
Finland	-0.35	-1.49	0.99%	0.12%
France	0.09	0.66	0.89%	2.23%
United Kingdom	-0.36	-3.45	0.82%	1.11%
Greece	-0.12	-2.57	0.09%	2.57%
Ireland	-0.05	-0.35	1.55%	1.72%
Italy	-0.03	-0.18	0.53%	1.08%
Japan	0.43	2.93	0.96%	3.97%
Netherlands	0.29	2.30	-0.002%	1.75%
New Zealand	-0.22	-1.30	-0.09%	4.90%
Sweden	0.06	0.56	0.40%	2.05%

TABLE 4.2

Industrial Sector	Correlation	t-stat.	Ave. TFP Growth Rate	Ave. IST Growth Rate
Primary	0.444755	0.600319	0.013061	0.02585
Mining and quarrying	-0.13522	-0.13445	0.004123	0.019507
Construction	0.545119	0.793985	-0.0184	0.02543
Manufacturing	0.364575	1.007994	-0.00354	0.027529
Electricity, gas and water	-0.09912	-0.2468	0.006498	0.030409
Transport and communications	0.169355	0.541571	0.05626	0.0455
Business and property services	0.091789	0.388129	-0.00964	0.07521
Personal and community services	0.017632	0.054999	0.015462	0.038775
Retail and wholesale trade	0.305878	0.915756	0.003513	0.040282

TABLE 4.3

	Coefficient	(t stat.)	Ave. TFP Growth	Ave. ICT diff. rate

SECTOR				
Agriculture	-0.3187	-0.5785	0.0184	0.1968
Mining	0.0026	0.0095	0.0318	0.2075
Manufacturing	-0.0299	-0.4306	-0.0027	0.2305
Electricity, Gas and Water	-0.0102	-0.0636	0.0339	0.1895
Construction	-0.2923	-1.3126	0.0026	0.2141
Retail Trade	-0.1518	-3.0050	-0.0169	0.2269
Wholesale Trade	-0.2126	-1.4738	0.0198	0.2159
Transport and Storage	-0.1942	-2.9127	0.0195	0.1927
Communications	-0.2518	-2.6261	0.0259	0.2183
Accommodation Cafés and Restaurants	-0.2833	-2.7934	-0.0376	0.2255
Finance and Insurance	0.0626	0.6501	0.0163	0.2207
Cultural and Recreational Services	-0.0550	-0.3794	-0.0589	0.2245