The Impact of High-Tech Capital on Productivity: Evidence from Australia

by

Ellis Connolly
Reserve Bank of Australia

and

Kevin J. Fox*
University of New South Wales

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Abstract
This paper examines the relationship between high-tech capital use and productivity. Using Australian data, some evidence is found of a positive relationship between high-tech capital use and productivity in the market sector, but there is much less evidence of excess returns. These results are robust to the use of a variety of different measures of high-tech capital. At the industry level however, the relationship is significant and positive for only some industries. This suggests that the benefits of investment in high-tech capital are not spread evenly across the economy.

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*Corresponding author:
Kevin J. Fox
School of Economics
University of New South Wales
Sydney 2052
Australia
Tel: +61-2-9385-3320
Fax: +61-2-9313-6337
K.Fox@unsw.edu.au

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1. Introduction

The bulk of the empirical research on the relationship between high-tech capital investment and productivity has been based on data for the U.S. Given the relatively large size of the high-tech capital sector in the U.S. economy, it is likely that the U.S. is a special case. Most economies resemble Australia’s in being net importers of high-tech capital. Not producing high-tech capital was often cited as a weakness in these economies relative to the U.S. However, since the end of the late 1990s tech boom, there has been a reappraisal of whether the production or the use of high-tech capital is most beneficial. Hence, to shed light on this debate, the main purpose of this paper is to empirically examine the relationship between high-tech capital use and the multi-factor productivity (MFP) of 10 industries in the Australian market sector.

There are three generally recognised ways in which investment in high-tech capital could increase output growth. First, through increased multi-factor productivity (MFP) in high-tech-producing industries; second, through capital accumulation in high-tech-using industries; and third, through increased MFP in high-tech-using industries. While the first two contributions are generally accepted, the third is more controversial, and is the focus of this paper. The focus is on the contribution from investment in high-tech capital to MFP rather than labour productivity, as labour productivity can also increase due to input substitution and high-tech capital accumulation (Simon and Wardrop, 2002; Stiroh, 1998). That is, it is a partial productivity measure, while MFP can more accurately reflect welfare gains to society.

Using annual data for 1966-2002, alternative specification of production functions are considered and estimated. Alternative measures of high-tech capital are included, with combinations of computers, software and electronics capital. In the first production function, high-tech capital is allowed to be more (or less) productive than other capital to determine whether there is a relationship between high-tech capital and MFP. It is also possible to test whether there are excess returns to high-tech capital. For robustness testing purposes, a second production function is specified with high-tech capital as a separate input into production. Other potential sources of MFP growth, such as public capital, research and
development stocks and microeconomic reform, are also included in the production functions.

We find evidence of a positive relationship between high-tech capital and MFP in the aggregate market sector. There is less evidence, however, of excess returns to high-tech capital, which suggests that current investment levels are not inadequate. The results by industry suggest that the benefits of investing in high-tech capital are not distributed evenly across the economy, with only some industries experiencing a positive relationship between high-tech capital and MFP.

The structure of this paper is as follows. In Section 2, the theoretical contribution of high-tech capital to MFP and the evidence to date is reviewed. In Section 3, the methodology is outlined. In Section 4, data sources and trends are described. In Section 5 the results are presented and interpreted. Section 6 considers limitations and possible extensions while Section 7 concludes.

2. The impact of high-tech capital on output and productivity: the theory and evidence

The impact of investment in high-tech capital has been the subject of debate between new economy sceptics and optimists for several years. It is widely accepted that MFP has increased substantially in U.S. high-tech producing industries, in which the rate of technological change has been phenomenal over the last forty years. The prediction made in 1965 by one of the founders of Intel, Gordon Moore, that the processing power of a silicon chip would double every 18 months has so far come true. This productivity improvement then increases aggregate productivity growth in proportion to the size of the high-tech producing industries. Several papers have found a quantifiable contribution by computer-producing industries to U.S. output growth.¹

However, Australia is not generally regarded as a producer of computers. Data from OECD (1998) indicate that the high-tech share of Australian manufacturing value added was 4.5 per cent in 1995, compared to 15.8 per cent in the U.S., placing Australia second last in
the OECD. The Industry Commission (1995a) Computer Hardware, Software and Related Service Industries Report states that Australia does not have a major capacity to manufacture computer components. Instead, the Australian information and communication technology (ICT) industry is primarily involved in the assembly of PCs and the provision of ICT related services. Therefore, the substantial U.S. economy-wide MFP improvements specifically associated with its computer-producing industry are unlikely to be replicated in the Australian economy.

Over the last thirty years, there has been rapid accumulation of high-tech capital in many countries. Australia was the third most intensive user of high-tech capital in the OECD in 1995 behind the U.S. and New Zealand. Simon and Wardrop (2002) find that this rapid accumulation of high-tech capital may have substantially contributed to Australia’s economic growth during the 1990s. This rapid accumulation has been driven by technological change in high-tech producing industries lowering the price of high-tech capital. Stiroh (1998) and Gordon (2000) argue that there is no evidence of non-traditional effects from this capital accumulation that would show up in MFP, and therefore conclude that the impact of computerisation on productivity in the computer-using sectors of the economy should be small.

‘New economy’ optimists such as Brynjolfsson and Hitt (1998) and Oliner and Sichel (2000) emphasise the ways in which the use of high-tech capital could improve aggregate MFP. First, investment in high-tech capital is complementary with new productivity-enhancing strategies and business processes such as the shift from mass production to mass customisation. Second, high-tech capital can be used to provide new services such as Automatic Teller Machines (ATMs), Electronic Funds Transfer Point of Sale (EFTPOS), Internet banking and shopping and e-procurement, which may provide more consumer satisfaction than the traditional labour intensive alternatives. Third, high-tech capital improves access to information which is essential for the efficient operation of markets and allocation of resources. Finally, the use of high-tech capital can increase the speed of innovation by making it possible to process the data required to develop new products faster and more cheaply.

1 See e.g., Oliner and Sichel (2000, 2003), Gordon (2000) and Jorgenson, Ho and Stiroh (2003).
Econometric studies in the US have had mixed success in finding a relationship between high-tech capital and MFP. Berndt and Morrison (1995) conducted a pioneering "exploratory analysis" of the impact of high-tech capital on the productivity of 2-digit classification U.S. manufacturing industries, and found little evidence of a relationship. Amato and Amato (2000) used data on U.S. manufacturing industries disaggregated to the 4-digit level, and also produced inconclusive results, suggesting that the "computer productivity paradox" is still alive and well. However, Lehr and Lichtenberg (1999) and Brynjolfsson and Hitt (2004) used firm-level data to find a significant positive impact on MFP from high-tech capital use.

Some recent studies comparing the European experience to that of the U.S. has revealed considerable differences (e.g. Oulton, 2002 and Salvatore, 2003). In a concise summary of the evidence, Daveri (2002) notes that it “looks as though the celebrated `Solow paradox’ on the lack of correlation between ICT investment and productivity growth has fled the USA and come to Europe.”

Few studies have directly examined the relationship between high-tech capital use and Australian MFP.2 Madden and Savage (1998), found that “investment in telecommunications and information technology,” proxied by main telephone lines per capita, is a significant short-run source of labour productivity growth for the Australian economy from 1950 to 1994. However this is not necessarily evidence of high-tech capital spillovers, since unlike MFP, labour productivity can increase due to capital accumulation.3 Colecchia and Schreyer (2002) use the methodology of Oliner and Sichel (1994, 2000) and Jorgenson and Stiroh (2000) applied to a data set of nine OECD countries, including Australia. They found that although Australia has a very small ICT producing sector, it has benefited markedly from ICT capital services. Supporting evidence was found by OECD (2003), NOIE (2004), and by Bassanini and Scarpetta (2002). Gretton, Gali and Parham (2002) used firm-level data to find “positive and significant links between ICT use and productivity growth in manufacturing and a range of service industry sectors.”4 However, these studies do not inform us of industry differences in the impacts of high-tech capital use, nor on the possible existence of excess

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2 Kraemer and Dedrick (1990), Dewan and Kraemer (2000) and Bean (2000) are cross-country studies into the impact of high-tech capital use on productivity. They include Australia, but do not report country-specific results.
3 Other papers which find a relationship between high-tech capital and labour productivity include Gera, Wu and Lee (1999) and Stiroh (2002b).
4 A shorter version of this paper is available as Chapter 6 of OECD (2004).
returns to high-tech capital investments. That is, high-tech capital typically has a higher user cost than other types of capital, which means that it must have a higher marginal product to make it a worthwhile investment, not simply contribute positively to growth (Lehr and Lichtenberg, 1999; Jorgenson and Stiroh, 1999; Stiroh, 2002). None of the above studies have examined this issue empirically for Australia.

3. Methodology

To measure the impact of high-tech capital on multi-factor productivity, Cobb-Douglas production functions are estimated. In the first function, high-tech capital is specified as a productivity enhanced form of capital, so we can assess whether it has made a significant contribution to multi-factor productivity (MFP). In the second function, high-tech capital is specified as a separate input, and the results between the different specifications are compared for robustness.

We begin with an aggregate production function specified as a function of technology and factor inputs:

\[ Y = A(t) f(K, L), \]  

where \( Y \) is a measure of real output, \( K \) is the private capital stock, \( L \) is a measure of labour input and \( A(t) \) represents disembodied technological change. This production function is specified to have a Cobb-Douglas functional form rather than a more flexible functional form, such as the CES or the Translog, since previous studies in Australia and elsewhere have found that the CES or Translog functional forms produce results virtually identical to those using a Cobb-Douglas functional form.\(^5\)

\(^5\) Dewan and Min (1997) and Lee and Barua (1999) find the Cobb-Douglas functional form yields output elasticities of high-tech capital to be virtually identical to those obtained using the Translog and CES production functions. Carmichael and Dews (1987) find that the CES function approximately collapses to a Cobb-Douglas when quarterly Australian data for the private sector, mining, manufacturing, finance and other industries are estimated. In addition, the Translog functional form often fails the required regularity conditions when estimated (Fox, 1996).
To explore whether investment in high-tech inputs is influencing MFP, a specification similar to Lehr and Lichtenberg (1999) and Schreyer (2000) is used, where the capital stock ($K$) is decomposed into high-tech capital ($K_H$) and non-high-tech capital ($K_N$). The output elasticity of capital ($\alpha$) is specified with respect to the 'effective' capital stock $[K_N + (1+\theta)K_H]$ where $\theta$ is a parameter measuring the extent to which a unit of $K_H$ is more (or less) productive than a unit of $K_N$. As high-tech capital typically has a higher user cost, it must have a higher marginal product to make it a worthwhile investment; see Section 3.2 below. The coefficient $\beta$ is the output elasticity of labour:

$$Y = A(t)[K_N+(1+\theta)K_H]^{\alpha}L^{\beta}. \quad (2)$$

To reduce the possibility that high-tech capital is positively correlated with an unobserved input that is more directly responsible for increased MFP, other inputs to production which have been found to be significant in other studies are included as regressors. Romer (1986) and Lucas (1988) argue that education can improve the ability of the labour force to adapt to new technology, resulting in higher productivity. To account for this, labour is decomposed into skilled ($L_H$) and unskilled labour ($L_N$), with the productivity enhancing effect of human capital being measured by the coefficient $\pi$ in equations (3)-(6) below. Industry Commission (1995) indicates that the Research and Development (R&D) stock is a significant variable in the Australian production function, while Otto and Voss (1994) find that the stock of public capital has a significant and positive impact on private sector productivity.

Griliches (1997) argues that environment variables which are not considered as standard inputs can also be included in the production function to reduce misspecification and omitted variables bias. The environment variables used in this study have all been used previously in studies of Australian output or productivity, and where possible, they have been customised for the relevant industry. To control for the role of microeconomic reform in Australia's improved productivity performance in the late 1990s, international competitiveness and openness are included. International competitiveness is measured using the terms of trade, which Otto (1999) finds has strong "predictive content" for Australian MFP. Openness is measured as Australia’s international trade, which according to Grossman and Helpman (1991), can also act as a carrier for international knowledge spillovers through foreign R&D. Other environment variables are: energy prices, to capture the impact of the three oil price
shocks on output; the weather as an influence on agricultural output; and a business cycle variable to account for the pro-cyclical nature of productivity. A time trend variable is also included to control for the effect of financial deregulation on MFP in finance and insurance. Further data details are given in Section 4 and Appendix A.

Therefore, the production function is augmented to include the R&D stock of a particular industry ($R$)\(^6\), public capital ($G$), and several environment variables, $Z_j$ where $j=1,2,...,n$. The parameters $\alpha$, $\beta$, $\psi$, $\gamma$ and $\varpi_j$ are the output elasticities of the respective inputs:

\[
Y = A(t)[K_N+(1+\theta)K_H]\alpha [L_N+(1+\pi)L_H]\beta R^\psi G^\omega \prod_{j=1}^n Z_j^{\varpi_j}.
\]

Taking the natural logarithm of equation (3),

\[
\ln Y = \ln A + \alpha \ln (K+\theta K_H) + \beta \ln (L+\pi L_H) + \gamma \ln R + \psi \ln G + \sum_{j=1}^n \varpi_j \ln Z_j + \kappa t,
\]

and by using the approximations $\ln(1+\theta K_H/K) \simeq \theta K_H/K$ and $\ln(1+\pi L_H/L) \simeq \pi L_H/L$ when $\theta K_H/K$ and $\pi L_H/L$ are small, (4) becomes an equation which can be estimated using ordinary least squares (OLS) if $\alpha \theta$ is treated as a single coefficient:

\[
\ln Y \simeq \ln A + \alpha \ln K + \alpha \theta K_H/K + \beta \ln L + \beta \pi L_H/L + \gamma \ln R + \psi \ln G + \sum_{j=1}^n \varpi_j \ln Z_j + \kappa t.
\]

Equation (5) can then be manipulated to produce an MFP specification. We assume constant returns to scale ($\alpha=1-\beta$), and subtract $\alpha \ln K + \beta \ln L$ from both sides, consistent with Solow (1957).\(^7\) MFP is then calculated using a standard growth accounting framework. In this framework, the factor share of income of labour is used as a proxy for the output elasticity of labour ($s_L=\beta$). Capital is then assumed to be the residual claimant on income ($s_K=1-s_L=1-\beta=\alpha$).\(^8\)

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\(^6\) If industry specific R&D data is unavailable, we use the domestic R&D stock.

\(^7\) An alternative to using capital stock data to calculate MFP is to use capital services data. However, since we only have high-tech capital stock data available, we use capital stock data rather than capital services data for consistency. In any case, the signs and significance of the results in Tables 1 and 2 are generally robust to the use of capital services instead of capital stocks in calculating MFP.

\(^8\) The labour and capital shares of income have been allowed to vary across industries and across time to obtain a more accurate measure of MFP. While this is desirable for estimation in (log) levels, expressing equation (6) in...
Therefore, we can see from equation (6) that in our productivity-enhanced inputs framework MFP is not only a function of disembodied technical change, but also R&D, government capital, environment variables, the high-tech share of capital and the skilled share of labour.

An alternative functional form specifies high-tech capital and skilled labour as separate inputs. If increases in high-tech variables have different returns-to-scale implications from the non-high-tech variables, and thus alter the shape of the production function, the production function could be specified as follows, where $a$, $b$, $c$, $d$, $e$, $f$ and $g$ are parameters which measure the output elasticities of their respective explanatory variables:

\[
Y = A(t)K_N^a K_H^b L_N^c L_H^d R^e G^f \prod_{j=1}^{n} Z_j^{g_j}.
\] (7)

This is similar to equation (14) of Stiroh (2002; p. 53), except here we consider a longer list of explanatory variables, including a separation of labour into skilled and unskilled. Taking the natural logarithm of both sides of equation (7), we arrive at an equation which can be estimated using OLS:

\[
\ln Y = \ln A + a \ln K_N + b \ln K_H + c \ln L_N + d \ln L_H + e \ln R + f \ln G + \sum_{j=1}^{n} g_j \ln Z_j + \kappa t.
\] (8)

This specification is more flexible than (6), which assumes an additive structure between $K_N$ and $K_H$. However, the difficulty involved in obtaining precise estimates of the output elasticities of capital and labour in small sample regressions leads us to prefer the results to equation (6) over the results to equation (8). Nevertheless, estimating equation (8) is a useful robustness check, since if $s_K \theta$ is statistically significant in (6), $b$ should also be significant in (8).
3.1 The Regression Equations

The models presented can be expressed as two linear regression equations which are estimated.\(^9\)

\[
\ln MFP_{it} = b_0 + b_1 K_{Hi}/K_t + b_2 L_{Hi}/L_t + b_3 \ln R_t + b_4 \ln G_t + \sum_{j=1}^{n} b_{5j} \ln Z_{ij} + b_6 t + \varepsilon_{1it}
\]

which corresponds to equation (6), and

\[
\ln Y_{it} = c_0 + c_1 \ln N_{Nit} + c_2 \ln K_{Hi} + c_3 \ln L_{Hi} + (1-c_1-c_2) \ln L_{Nit} + c_4 \ln R_t + \sum_{j=1}^{n} c_{7j} \ln Z_{ij} + c_8 t + \varepsilon_{2it}
\]

which corresponds to equation (8) with constant returns to scale imposed.

For industry \(i\) in period \(t\), \(Y_{it}\) is output, \(K_{it}\) is the capital stock, \(K_{Hi}\) is the high-tech capital stock, \(N_{Nit}\) is the non-high-tech capital stock, \(L_{it}\) is labour input, \(L_{Hi}\) is skilled labour, \(L_{Nit}\) is unskilled labour, \(R_{it}\) is the R&D stock of the \(i^{th}\) industry, \(G_t\) is the government capital stock, \(Z_{ijt}\) is environment variable \(j\), and \(a_x, b_x\) and \(c_x\) are unknown parameters where \(x=1,2,\ldots,X\). To preserve degrees of freedom, we exclude environment variables which are individually insignificant at the 15 per cent level.

The coefficient \(b_1\) on \(K_{Hi}/K\) indicates the sign of the relationship between MFP and the share of high-tech capital in the total capital stock. Since the relationship is log-linear, the slope and elasticity change for each value of \(K_{Hi}/K\) and MFP, but they always have the same sign as the coefficient.

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\(^9\) In Connolly and Fox (2003), the working paper version of this paper, results were also presented for a regression corresponding to equation (5). However, the estimated output elasticities of capital and labour were often counterintuitive. Therefore the results for the MFP specification in equation (9) are preferred.
The coefficient \( b_1 \) can be used to derive an estimate of \( \theta \), the extent to which high-tech capital is more productive than other capital, weighted by the output elasticity of \( K \). From (9) it is possible to calculate \( \theta \) using the formula \( b_1 \approx s_K \theta \) derived from equation (6), using capital’s share of income as a proxy for the output elasticity of capital. Then if we assume capital’s share of income is known with certainty, we can derive the standard error of \( \theta \) from the standard error of \( b_1 \).\(^{10}\) We can then conduct hypothesis tests on whether there are excess returns to high-tech capital relative to other capital. Lehr and Lichtenberg (1999) did not derive such standard errors and so did not conduct the relevant hypothesis tests.

Regression equation (10), which is based on equation (8), estimates output with high-tech capital and human capital as separate inputs. From (10), we can obtain \( c_2 \), the output elasticity of \( K_H \). While the magnitude of \( c_2 \) is not directly comparable with \( b_1 \), we would expect a positive coefficient on \( b_1 \) would coincide with a positive coefficient on \( c_2 \). For consistency with equation (9), constant returns to scale are imposed in equation (10).\(^{11}\) Public capital is excluded as a regressor in equation (10) since potential collinearity with private capital inhibits our ability to accurately estimate the output elasticity of capital.

### 3.2 Quantifying the returns to high-tech capital

By differentiating (3) with respect to \( K_H \), it is possible to calculate the marginal product of high-tech capital (\( MPK_{HI} \)):

\[
MPK_{HI} = A(t)[L_N + (1+\pi)L_H]^{\beta}R^ZG^{\omega} \prod_{j=1}^{n} Z_j^{\omega_j} \alpha(1+\theta)[K_N + (1+\theta)K_H]^{\alpha-1} = \frac{\alpha(1+\theta)Y}{K_N + (1+\theta)K_H} \tag{11}
\]

which can then be compared to the marginal product of other capital:

\[
MPK_{NI} = \frac{\alpha Y}{K_N + (1+\theta)K_H} \tag{12}
\]

\(^{10}\) In Connolly and Fox (2003), \( \theta \) was calculated using the estimated output elasticity of capital, and the standard error of \( \theta \) was calculated using a Taylor series expansion. The standard error of \( \theta \) was much wider due to our imprecise estimates of the output elasticity of capital.

\(^{11}\) When constant returns to scale are not imposed, some of the estimated output elasticities are implausible.
Lehr and Lichtenberg (1999) note that the ratio of the marginal products of high-tech capital and other capital \( \frac{MPK_{H1}}{MPK_{N1}} \) for the profit maximising industry should equal the ratio of the user costs of high-tech capital and other capital \( \frac{R_H}{R_N} \):

\[
\frac{MPK_{H1}}{MPK_{N1}} = (1 + \theta) = \frac{R_H}{R_N} = \frac{(r + d_H - E(p_H))P_H}{(r + d_N - E(p_N))P_N}
\]  

(13)

where \( r \) is the risk-adjusted discount rate, \( d_m \) is the depreciation rate, \( P_m \) is the purchase price of a unit of capital, and \( E(p_m) \) is the expected rate of price appreciation where \( m=H \) for high-tech capital and \( m=N \) for other capital. This relationship can be used to test whether the returns to high-tech capital in Australian industries equal the returns to other capital, as follows.

Using data from the Australian Bureau of Statistics (ABS) on computer capital (see Section 4), the following values were calculated: \( d_H = 0.20, \ d_N = 0.05 \), which are the average depreciation rates from the ABS; \( E(p_H) = -0.15, \ E(p_N) = 0.6 \), where \( E(p_H) \) captures the trend in computer prices and is estimated by taking the long-run average price change; \( r = 0.04 \), as used by the ABS; and \( P_H/P_K \) is normalised to 1. The ratio of user costs in equation (13), \( R_H/R_N \), is then 13, implying \( \theta = 12 \). Thus, a test of the null hypothesis \( H_0: \theta = 12 \) is a test of no excess returns to computers (see Lehr and Lichtenberg, 1999; p. 337). We consider different types of high-tech capital, so each may have a different ratio of user costs. For an aggregate of ‘computers and software’ capital, the ratio turns out to be the same as for computers, so that a test of the null hypothesis \( H_0: \theta = 12 \) is also a test of no excess returns to computers and software. For an aggregate of ‘electronics, computers and software’ capital, \( d_H = 0.15 \) and \( E(p_H) = -0.01 \), as electronics dominates this aggregate. In this case, a test of the null hypothesis \( H_0: \theta = 5 \) is a test of no excess returns to electronics, computers and software.

As noted by Lehr and Lichtenberg (1999; p. 357), a test for excess returns is much stronger than a test of whether high-tech capital is productive. If excess returns to capital are found, then this implies that profit-maximising firms should be utilising high-tech capital relatively more intensively.
There are two weaknesses inherent in this method of quantifying the returns to high-tech capital. First, \( R_H/R_N \) is based on the assumption of profit maximising behaviour at the firm level. However, we are dealing with industries, which are not decision-making units. Therefore any economic theory that is applicable to the firm may not be applicable to the industry. Second, the additive framework for capital \( [K = K_N + (1 + \theta)K_H] \) implies that \( R_H/R_N \) (the ratio of marginal products) is constant over time if \( \theta \) is constant, which is a strong assumption, especially considering the rapid technological progress embodied by high-tech capital. Nevertheless, this calculation can give us an approximate comparison of the returns to high-tech capital relative to other capital.

For equation (7), which specified high-tech capital as a separate input into production, we can also calculate the respective marginal products for high-tech and other capital, \( MPK_{H2} \) and \( MPK_{N2} \):

\[
MPK_{H2} = \frac{\partial Y}{\partial K_H} = \frac{bY}{K_H} \\
MPK_{N2} = \frac{\partial Y}{\partial K_N} = \frac{aY}{K_N}
\]

(14) (15)

It is then possible to compare the estimated values of these marginal products to those from using (11) and (12).

4. **Data construction, measurement issues and trends**

4.1 **Data Construction**

The Australian Bureau of Statistics (ABS) calculates annual capital (net capital stocks), labour (total hours worked) and output (value added) data for Australian industries under the Australian and New Zealand Standard Industrial Classification (ANZSIC). Unfortunately, only data for industries in what the ABS defines as the ‘market sector’ can be used in this paper because these are the only ones for which output is not calculated as a function of

\[\text{[12] Details on data sources and definitions are provided in Appendix A.}\]
labour input. All yearly observations are from 1 July of the previous year until 30 June ‘current’ year. Such data are available for ‘agriculture, forestry and fishing’, ‘mining’, ‘manufacturing’, ‘electricity gas and water supply’, ‘construction’, ‘wholesale and retail trade’ and ‘transport, storage and communications’ from 1965/66-2001/02 and for ‘accommodation, cafes and restaurants’, ‘finance and insurance’ and ‘cultural and recreational services’ from 1974/75-2001/02.13

The ABS has recently calculated the net capital stocks of ‘electronics, electrical machinery and communications equipment’ (referred to as electronics), ‘computer equipment and peripherals’ (referred to as computers) and ‘software’ for each of the industries back to 1959/60.14 Since these three forms of capital could each be considered high-tech, but are derived from different data sources by the ABS, three alternative measures of high-tech capital are used in this paper to improve the robustness of the results: ‘electronics, computer and software capital stocks’, ‘computer and software capital stocks’, and ‘computer capital stocks’.15

Other variables are constructed as follows. Similar to the approach of Otto and Voss (1994), the general government net capital stock is used as the measure for public capital, and is included in regressions for predominantly private sector industries.16 R&D expenditure data is available from the ABS for 1976/77-2001/02 for ‘mining’, ‘manufacturing’, ‘wholesale and retail trade’, ‘finance and insurance’ and the domestic economy, and is used to calculate R&D stocks for those industries and the domestic economy using the perpetual inventory method.17 The dearth of industry-specific education data in Australia precludes the inclusion of human capital in regressions for each industry in the market sector, but at the aggregate level, a measure of the proportion of employed with further education from the ABS is used. The ANZ vacancies series is the measure of the business cycle (Foster, 1996; ANZ, 2003).

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13 Data are also available for “transportation and storage”, “communications”, “wholesale trade” and “retail trade” from 1974/75 – 2001/02. However, to lengthen the time series back to 1965/66, these industries have been aggregated into “transport, storage and communications” and “wholesale and retail trade”.
14 The ABS has also calculated productive capital stocks. When productive capital stocks are used in the regressions rather than net capital stocks, the results are very similar, since the productive capital stocks and the net capital stocks have a correlation of 0.99 for all industries.
15 These series are constructed by the authors using Törnqvist quantity indices.
16 Predominantly private sector industries are: agriculture, mining, manufacturing and wholesale and retail trade.
17 The results presented in section 5 use R&D stocks data with a depreciation rate of 5%. The use of alternative depreciation rates were not found to affect the results.
Alternative measures of the terms of trade are used where most appropriate.\textsuperscript{18} The quantity of imports and exports is the measure for openness and is used in the market sector regressions. The West Texas crude oil price is the measure of energy prices and is included in all regressions. Finally, the Southern Oscillation Index from the Bureau of Meteorology is included as a measure of the weather in the agriculture regressions to reduce weather-induced volatility.

4.2 Data measurement issues

Mis-measurement is often sighted as a cause of the ‘computer productivity paradox’; see e.g. Griliches (1994), and Diewert and Fox (1999; 2001). Triplett (1999) and David (1999) both note the difficulty involved in measuring high-tech capital and the output of service industries, which tend to have the largest proportions of high-tech capital in their capital stocks. However, Triplett and David both conclude that mis-measurement biases are not sufficient to explain away the computer productivity paradox.

The problem of measuring the true quantity of computer capital when prices fall due to rapid technological change has encouraged Triplett and the U.S. Bureau of Economic Analysis (BEA) to construct hedonic price indices for computers. In hedonic regressions, the price of computers is regressed on the relevant quality characteristics. The prices are then adjusted to incorporate the effect of technology changes. The ABS uses the BEA’s quality-adjusted computer price index in calculating the computer net capital stock for each industry. Unfortunately, hedonic indices are very expensive for statistical agencies to produce, and at this stage, the price indices for software and electronics are not constructed using hedonic methods.\textsuperscript{19} Nordhaus (2001) even suggests that these hedonic price indexes do not capture all the price declines in computers, since they focus on inputs rather than output. Any measurement error resulting from insufficient quality adjustment of software and electronics capital could then appear as an MFP spillover.

\textsuperscript{18} Terms of trade in ‘goods’ is used for agriculture, mining and manufacturing, ‘services’ is used for other industries, while ‘goods and services’ is used for the market sector.
\textsuperscript{19} The BEA now has official quality-adjusted deflators for pre-packaged software, but the ABS is still working on producing a price index for computer software.
The use of high-tech capital tends to be concentrated in industries where measurement problems are thought to be greatest. For example, ‘construction’, ‘finance and insurance’ and ‘wholesale and retail trade’ could suffer from output mis-measurement. Triplett and Bosworth (2001) note that increased customer satisfaction due to the introduction of new products such as ATMs and Internet banking does not contribute to output in finance and insurance. The Industry Commission (1995b) notes that the progression away from street shopping to chain stores and the introduction of improved inventory management techniques may not be adequately incorporated into the ABS wholesale and retail trade output statistics. In David (1999) it is argued that the economy is fundamentally changing from a mass production to a mass customisation orientation, involving more quality change and price differentiation than our statistical systems are designed to handle. Diewert and Fox (1999) provide evidence of the increasing proliferation of new outputs, with the number of products in the average grocery store more than doubling between 1972 and 1994. If output is indeed becoming more difficult to measure over time, one would expect it to be harder to find a relationship between the recent rapid increase in high-tech capital and MFP.

4.3 Data trends

The 10 industries in our sample, which sum to the market sector, accounted for around 55 per cent of Australian gross domestic product in 2000/01, the base year. The largest industry, manufacturing, represented 20 per cent of the market sector, while the smallest, ‘cultural and recreational services’, was 3 per cent of the market sector (Table 1). The average capital share of income for most industries ranged between 30 per cent and 50 per cent, while ‘mining’, ‘electricity, gas and water’ and ‘agriculture’ were more capital intensive. The high-tech intensity (ratio of high-tech capital to total capital) of the market sector was 7 per cent in 2000/01, with ‘finance and insurance’, and ‘cultural and recreational services’ the most high-tech intensive, while ‘agriculture’ and ‘mining’ were the least high-tech intensive. Some of these service industries, including ‘finance and insurance’ and ‘wholesale and retail trade’, experienced an improvement in their MFP performance during the 1990s (Figure 1).

20 The base year is the only year for which the sectors can be (legitimately) simply summed, without using an index number formula for aggregation.
5.  Econometric Issues and Results

Several methods have been used to estimate equations (9) and (10), including Ordinary Least Squares (OLS), Seemingly Unrelated Regressions (SUR) and panel regressions. Panel-data techniques are found to be inappropriate.\(^{21}\) The OLS results are reported rather than the SUR results because the OLS results do not suffer from possible misspecification in one regression contaminating a whole system. However, the OLS and SUR results are similar.

5.1  Econometric problems and diagnostic testing

Endogeneity is a potential problem in time-series regressions. If labour, measured by hours worked, is an endogenous regressor when output is the regressand, the results from equation (10) will be biased. A solution would be to use instrumental-variables estimation with an instrument for labour. However there do not appear to be any good instruments available for labour over the required time period.\(^{22}\) In any case, the results from estimating equation (9) will not suffer from this potential endogeneity, since labour has been incorporated into the regressand, MFP. The business-cycle variable, which is the ANZ job vacancies series, is unlikely to be endogenous because it has a tendency to lead output and would therefore be predetermined.

Equations (9) and (10) involve the use of time-series data in (log) levels, which could be non-stationary. With a larger sample size, it would be more feasible to check for unit-roots and cointegration. However, given sample sizes that are no greater than 37, such testing is of little value and generally does not reject the null hypothesis of a unit root. Therefore, the approach of Otto and Voss (1994) is followed. They augment their models with a linear time trend, which would be appropriate if the data are trend stationary and not detrimental if the data are

---

\(^{21}\) F tests on the restriction of equal slope coefficients on \(K_{H}/K\) across industries are rejected at the 1% significance level for all three \(K_{H}\) proxies. Therefore the OLS results should be preferred to the panel results since they do not impose equality restrictions on the \(K_{H}/K\) coefficient across industries.

\(^{22}\) Hausman tests suggest that there are not significant endogeneity problems in our results when the lag of labour and the other variables in the regressions are used as instruments for labour in equation (10) without imposing constant returns to scale. Instrumenting for labour also does not appear to affect the significance of the coefficients on high-tech capital.
in fact difference stationary. The Durbin-Watson test statistics provide informal evidence that suggests that the regressions are not spurious.\textsuperscript{23} Another alternative is to estimate equations (9) and (10) in differences, without a time trend. According to Box and Jenkins (1970), this approach has the advantage of being appropriate if the data are difference stationary. However this approach inhibits estimation of the long-run relationship between high-tech capital and productivity, since any common long-run stochastic trends in the data are removed by differencing. For the same reason, differencing may also accentuate problems with endogeneity. However, for completeness and comparison purposes, the results for equations (9) and (10) estimated in differences are presented in Appendix B.

Several other standard diagnostic tests are also reported: the p-values for White heteroskedasticity tests without cross-terms; the test statistic for the Durbin-Watson test for autocorrelation and p-values for the Jarque-Bera test for normality. Generally, there is little evidence of heteroskedastic, autocorrelated or non-normal residuals.

5.2 Results for the regression equations

Data measurement issues aside, anecdotal evidence suggests that one would expect to find service sectors to have benefited more from the investment in high-tech capital, given that these industries use high-tech capital more intensively. Thus, \textit{a priori}, we would expect an industry such as ‘finance and insurance’ to have benefited more than say ‘agriculture’. Stiroh (2002; p. 54) notes that while the evidence of spillover effects in manufacturing are weak for the U.S., “it is possible that different ICT effects are present in other more intensive users of ICT, so work on other industries or countries is needed to corroborate these findings.”

For each industry, the results using ‘electronics, computers and software’ as the measure for high-tech capital are presented for equation (9) in Table 2. There is a positive coefficient significant at the 10 per cent level on $K_{HI}/K$ for the market sector, which suggests that in aggregate, high-tech capital is more productive than other capital in the measurable industries of the Australian economy. This finding is supported by the individual sectoral results, where there is a positive and significant relationship between the high-tech share of capital and MFP in wholesale and retail trade, construction, agriculture, finance and insurance and

\textsuperscript{23} For more on the use of the Durbin-Watson test statistic in this context, see e.g., Otto and Voss (1994)
accommodation, cafes and restaurants at the 10 per cent level. These results are robust to the use of the alternative measures of high-tech capital.

Significant coefficients on the high-tech share of capital in service industries are particularly noteworthy considering that output mis-measurement in these industries would be expected to reduce our ability to find a relationship with MFP. However, if the method of quality adjustment of high-tech capital used by the ABS underestimates quality change, part of the benefit of accumulating high-tech capital would be included in MFP. This could help to explain the relationship. Alternatively, the coefficients may be capturing some of the productivity benefits of deregulation in these industries over the last 15 years, which has coincided with increased high-tech investment. This does not appear to be the case for finance and insurance – a trend dummy has been included from 1986/87 to capture the productivity enhancing effect of financial deregulation, and the coefficient on high-tech capital is still significant. However, the results for ‘wholesale and retail trade’ and ‘accommodation, cafes and restaurants’ may suffer from misspecification, as suggested by low Durbin-Watson statistics and evidence of heteroskedasticity. It is harder to develop variables to capture the effect of deregulation in these sectors, where the reforms were conducted at the State government level at different points in time.

There are, however, several industries which do not appear to be benefiting from the productivity enhancing effects of using high-tech capital. In ‘manufacturing’, ‘transport, storage and communication’, and ‘cultural and recreational services’, the coefficient on high-tech capital is insignificant. In electricity, gas and water, and mining, there is actually evidence of a negative relationship between high-tech capital and productivity. However the result for mining is not robust to the use of the narrower measures of high-tech capital. Structural changes in these industries may be affecting our results. In particular, ‘electricity, gas and water’, and ‘transport, storage and communication’ underwent substantial restructuring in the 1990s, which may be inhibiting our efforts to identify the contribution of high-tech capital to MFP.

The robustness of these results can be tested by estimating equation (9) for each industry in differences rather than levels; see Table B1 in Appendix B. The signs of the coefficients are consistent with Table 2 for most industries. However, the standard errors are much larger,
which is unsurprising, since these regressions are only estimating the short-run relationship between the high-tech share of capital and MFP.

Our alternative specification is equation (10), which specifies high-tech capital as a separate input into production. If there is a significant relationship between high-tech capital and MFP in equation (9), one would also expect high-tech capital to have a significant output elasticity, since MFP growth is one of the drivers of output growth. The results are presented in Table 3. The results for the market sector, ‘finance and insurance’ and ‘agriculture’ are positive and significant at the 10 per cent level, consistent with the results in Table 2. Also consistent are the results for ‘manufacturing’, ‘cultural and recreational services’ and ‘transport, storage and communication’, with small or insignificant contributions, and ‘mining’ and ‘electricity gas and water’, with negative contributions. However, the results for ‘wholesale and retail trade’, ‘construction’ and ‘accommodation, cafes and restaurants’ are harder to reconcile. For these industries, we tend to prefer the results in equation (9), which impose more plausible output elasticities of capital.

Results for equation (10) in differences are presented in Appendix Table B2. While the signs of the coefficients are generally consistent with those presented in Table 3, again the standard errors are much larger, and many of the output elasticities on other capital and labour are counterintuitive.

Overall, the results are broadly consistent with those from previous studies in the U.S., and suggest a stronger relationship between high-tech capital and MFP than has been previously estimated for Australian data. The positive significant coefficients on high-tech capital in Australian service industries are similar to the findings in overseas studies such as Brynjolfsson and Hitt (1998) and Lehr and Lichtenberg (1999). Previous studies into the determinants of Australian productivity, such as Kraemer and Dedrick (1990) and Madden and Savage (1998) did not have access to the new ABS capital stock data which have allowed us to obtain more robust estimates of the relationship between high-tech capital and productivity.

The results for non-service industries such as mining and manufacturing are also consistent with the US evidence, where Berndt and Morrison (1995), Amato and Amato (2000), and
Stiroh (2002) were unable to find a relationship between high-tech capital and manufacturing productivity in the US. While heterogeneity may also be affecting the manufacturing results for Australia, Amato and Amato (2000) were unable to find a relationship even when the manufacturing industry is disaggregated to the four digit level.

The results for the other variables specified in the equations are broadly similar to those in previous studies. The coefficients on the human capital variables are insignificant in the market sector regressions, a result which is consistent with Gust and Marquez (2000) and Bassanini, Scarpetta and Visco (2000), suggesting that the failure to specify human capital in the industry-level regressions should not be a major source of bias. Also, public capital has a positive and significant output elasticity in the manufacturing and wholesale and retail trade industries in Table 2, consistent with the findings of Otto and Voss (1994).

### 5.3 The marginal product of high-tech capital, and the returns to high-tech capital

We also make an attempt to quantify the marginal product of high-tech capital and test whether there are excess returns to high-tech capital under the first-order conditions of profit maximisation. As noted in Section 3.2, estimates for $\theta$, the extent to which high-tech capital is more productive than other capital, are calculated by dividing the coefficient on the high-tech share of capital, $b_1$, by $s_K$ the output elasticity of capital, proxied by capital’s share of income. The calculations for each industry using the different measures of high-tech capital are reported in Table 4.

The dispersion of $\hat{\theta}$s is inversely related to the high-tech share of capital, suggesting that the estimates of $\hat{\theta}$ are more accurate for industries with a higher share. Alternatively, there may be diminishing returns to investment in high-tech capital. This may help to explain why industries such as ‘agriculture’ and ‘accommodation, cafes and restaurants’, which have very small high-tech shares of capital can have such large $\hat{\theta}$ values.

The marginal product of high-tech capital in equation (9) is calculated at each point in time:
\[
MPK_{HI} = \frac{\alpha(1+\theta)Y}{K_N + (1+\theta)K_H}
\]

where \(\alpha\) is proxied by \(s_K\) and \(\alpha \theta\) is estimated by \(b_1\). As noted in Section 3.2, implicit in \(MPK_{HI}\) is the assumption that \(\theta\) is constant over time, which is a strong assumption to be making over a minimum 25 year period. We can also calculate the marginal product of high-tech capital using estimates of (10) and the formula: \(MPK_{H2} = bY/K_H\), where high-tech capital is specified as a separate input. \(MPK_{HI}\) is plotted in Figure 2 using ‘electronics, computers and software’ as the measure of high-tech capital for the market sector and the industries with the most robust results.\(^{24}\)

For the market sector, \(MPK_{HI}\) is downward sloping, falling from 132 per cent in 1974/75 to 106 per cent in 2001/02. It is reasonable to expect \(MPK_{HI}\) to fall over time as \(K_H/K\) rises, as diminishing returns to high-tech capital begin to set in. The marginal product of other capital, \(MPK_{NI}\), is around 15 per cent, and is much smaller than the corresponding \(MPK_{HI}\) values. This is to be expected, since high-tech capital has a significantly shorter functioning life than other forms of capital. When we compare \(MPK_{HI}\) and \(MPK_{H2}\), we find broadly similar results, with \(MPK_{H2}\) of 160 in 2001/02. At the industry level, for those industries with a positive output elasticity of high-tech capital, the results display the same downward slope, but \(MPK_{H2}\) tends to be somewhat higher than \(MPK_{HI}\). This is unsurprising, since the estimated output elasticities of capital for these industries are higher in equation (10) than those imposed in calculating MFP in equation (9).

As noted in Section 3.2, the relationship in equation (13) can be used to test whether there are excess returns to high-tech capital. Null hypotheses are formulated for the three different measures of high-tech capital.\(^{25}\) For ‘electronics, computers and software’ capital, \(H_0: \theta = 5\), while for ‘computers and software’ capital and ‘computers’ capital, \(H_0: \theta = 12\). The latter null is higher due to a faster depreciation rate, and larger expected price declines; see Section 3.2 for more details.

\(^{24}\) The results for ‘computers and software’ and ‘computers’ are similar to the ‘electronics, computers and software’ results except with larger values of \(MPK_{HI}\) and \(MPK_{H2}\).

\(^{25}\) The use of three different measures reduces the sensitivity of the magnitude of \(\theta\) to an arbitrary definition of \(K_H\).
The $p$-values for the hypothesis tests for each industry are presented in Table 3 (and the results from estimating equation (9) in differences are presented in Table B3). There is little evidence of excess returns to high-tech capital across our three measures of high-tech capital for the market sector, and for most industries. Only in ‘agriculture’ and ‘accommodation, cafes and restaurants’ is there consistent evidence of excess returns across the three measures of high-tech capital. Both these industries have relatively low high-tech intensities, and the result suggests they could benefit from further investment in high-tech capital. However, there is also evidence of deficient returns to high-tech capital in ‘manufacturing’, ‘electricity, gas and water’, ‘finance and insurance’ and ‘cultural and recreational services’, suggesting that these industries may have over-invested. Consistent with this, some of these industries are relatively high-tech capital intensive. Overall, the results suggest that the benefits of further investment in high-tech capital are not spread evenly across the economy.

6. Limitations and possible extensions

There remains wide scope for the relationship between high-tech capital and productivity to be explored in future research. This paper is limited by the number of data points available for Australian high-tech capital. This has led to the use of the Cobb-Douglas functional form, which is relatively restrictive, and has resulted in quite large standard errors on our estimates. With additional observations and capital rental-price data, a more flexible approach could be adopted with, e.g. Translog cost or profit functions. The analysis has also been limited to the Australian market sector, which excludes key industries such as education, health and government, where the use of computers has the potential to significantly influence productivity.

This paper has not attempted to explicitly model the impact of the Internet and e-commerce since it is very difficult to explicitly measure its effect on productivity at this early stage. Methodologies for measuring the productivity gains from e-commerce and the Internet are only in their infancy and are beyond the scope of this paper. Nevertheless, much of the impact of the Internet should be captured by the high-tech variables used here, which include the hardware and software requirements of the Internet. Some of the effects that network externalities from the Internet might be having on the economy should eventually be reflected in output through the measurement of final goods and services.
7. Conclusion

This paper has presented an analysis into the relationship between high-tech capital and Australian multi-factor productivity (MFP). This is an important topic given the debate on whether the benefits of computerisation lie in their production or their use. It is well accepted that the production of computers involves strong MFP growth. However, whether using computers increases MFP remains controversial. Since Australia is a relatively computerised society but, like most countries, a net importer of high-tech capital, it is particularly important to explore whether the use of high-tech capital is a source of increased MFP.

The contribution of high-tech capital use to the productivity of 10 market sector industries of the Australian economy was measured by estimating production functions with different specifications of capital embodied technical change. The robustness of the results was tested using different measures of high-tech capital and other inputs which may impact on MFP. The marginal product of high-tech capital was calculated and compared to the marginal product of other capital for the different specifications. Finally, it was possible to test whether there are excess or deficient returns to high-tech capital under the assumption of profit-maximising behaviour.

For the Australian market sector, there is some evidence of a relationship between high-tech capital use and MFP. At the industry level, the results indicate that the benefits of investment in high-tech capital are not spread evenly across the economy. The industries with evidence of a positive relationship between high-tech capital use and productivity are ‘wholesale and retail trade’, ‘finance and insurance’, ‘accommodation, cafes and restaurants’ and agriculture. However for ‘electricity, gas and water’, there is some evidence of a negative relationship. These results are somewhat surprising, with positive relationships being found in service industries where output measurement is generally thought to be most problematic.

Since productivity is one of the main drivers of economic growth, these results may have implications for economic policy. If the strong productivity growth in Australia during the 1990s is partly due to contributions from investment in high-tech capital, then it is more likely...
that this improved productivity performance is structural rather than cyclical. However, whether further investment in high-tech capital should be encouraged across all sectors of the economy is an area for further research, with the returns to high-tech capital appearing to vary substantially between industries.
Appendix A: Data Sources

Computers and computer peripherals net capital stocks: ABS Cat. No. 5204.0. Includes computers, line printers and VDUs.

Software net capital stocks: ABS Cat. No. 5204.0. The ABS use data for capital formation in computer software.

Electronic and electrical machinery and communication equipment net capital stocks: ABS Cat. No. 5204.0. Electronic and electrical machinery and communication equipment includes business machines (automatic teller machine (ATM); calculators; cash registers; office machines; photocopiers; typewriters), Telecommunication, broadcasting equipment (modems; radio receivers and transmitters; telephone equipment; television studio equipment), Electronic equipment, Household appliances, Electrical cable and wire, Battery, Electric lights and signs.

Value added by industry: ABS Cat. No. 5204.0 and ABS Cat. No. 5211.0.


Net capital stocks by industry: ABS Cat. No. 5204.0


R&D expenditure by industry and product field: ABS Cat No. 8104.0 for 1977-2002. From 1976/77 to 1984/85, the ABS only ran a comprehensive Survey of Research and Experimental Development every second year, requiring the use of linear interpolation to fill in the gaps.

Employed (15-64) with post school qualifications: ABS Cat. No. 6227.0 and ABS Cat. No. 6504.0, with interpolation for 1975-1976.

Public capital: ABS Cat. No. 5204.0 general government net capital stock

Terms of trade: ABS Cat. No. 5302.0.

Energy price index: West Texas crude oil prices (Bloomberg).

ANZ job vacancies: Foster (1996) and ANZ (2001)

International trade: calculated as a Fisher index of exports plus imports. ABS Cat. No. 5302

Weather: Southern Oscillation Index (Australian Bureau of Meteorology)
Appendix B: Supplementary Tables

(Attached)
References


Table 1: Value added and high-tech capital in the Australian market sector

<table>
<thead>
<tr>
<th>Market sector</th>
<th>Value added in 2001 (A$ billion)</th>
<th>Average capital share of income (%)</th>
<th>High-tech intensity in 2001</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manufacturing</td>
<td>73.4</td>
<td>35.0</td>
<td>6.1</td>
</tr>
<tr>
<td>Mining</td>
<td>34.0</td>
<td>67.9</td>
<td>1.0</td>
</tr>
<tr>
<td>Transport, Storage and Communication</td>
<td>51.6</td>
<td>42.9</td>
<td>6.8</td>
</tr>
<tr>
<td>Electricity, Gas and Water</td>
<td>15.4</td>
<td>61.7</td>
<td>7.0</td>
</tr>
<tr>
<td>Wholesale and Retail trade</td>
<td>66.4</td>
<td>34.3</td>
<td>10.7</td>
</tr>
<tr>
<td>Construction</td>
<td>34.9</td>
<td>47.7</td>
<td>8.1</td>
</tr>
<tr>
<td>Agriculture</td>
<td>21.6</td>
<td>80.5</td>
<td>3.6</td>
</tr>
<tr>
<td>Finance and insurance</td>
<td>44.9</td>
<td>38.8</td>
<td>12.4</td>
</tr>
<tr>
<td>Accommodation, Cafes and Restaurants</td>
<td>14.7</td>
<td>29.2</td>
<td>5.5</td>
</tr>
<tr>
<td>Cultural and Recreational Services</td>
<td>11.8</td>
<td>42.4</td>
<td>13.8</td>
</tr>
<tr>
<td>Market sector</td>
<td>368.6</td>
<td>45.1</td>
<td>6.7</td>
</tr>
</tbody>
</table>

High-tech intensity in 2001:
- Electronics: 2.1, 0.7, 5.0, 6.0, 4.6, 3.7, 2.9, 1.7, 3.1, 3.5, 10.0, 3.8
- Computers: 2.0, 0.1, 1.0, 0.7, 2.4, 1.7, 0.3, 7.6, 1.0, 2.1, 1.2
- Software: 2.0, 0.2, 0.9, 0.3, 3.7, 2.8, 0.4, 1.0, 1.6, 1.7
Table 2: Results for equation (9)

<table>
<thead>
<tr>
<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and Insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Market sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Electronics, computers &amp; software) / capital (KH/K)</td>
<td>-0.233 (0.558)</td>
<td>-29.253 (0.054)</td>
<td>0.918 (0.304)</td>
<td>-9.423 (0.000)</td>
<td>8.362 (0.000)</td>
<td>7.219 (0.001)</td>
<td>30.573 (0.002)</td>
<td>0.876 (0.002)</td>
<td>14.235 (0.001)</td>
<td>0.734 (0.305)</td>
<td>3.046 (0.000)</td>
</tr>
<tr>
<td>Public capital</td>
<td>0.150 (0.025)</td>
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<td>0.710 (0.000)</td>
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<tr>
<td>R&amp;D</td>
<td></td>
<td></td>
<td>-0.079 (0.112)</td>
<td>0.076 (0.004)</td>
<td>0.080 (0.029)</td>
<td>-0.138 (0.054)</td>
<td>0.053 (0.001)</td>
<td>-0.485 (0.000)</td>
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<tr>
<td>Business cycle</td>
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<tr>
<td>Energy prices</td>
<td>0.017 (0.056)</td>
<td>0.031 (0.005)</td>
<td>-0.029 (0.036)</td>
<td>0.041 (0.027)</td>
<td>0.066 (0.003)</td>
<td>-0.055 (0.083)</td>
<td></td>
<td></td>
<td>0.020 (0.13)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terms of trade</td>
<td>0.568 (0.000)</td>
<td>0.487 (0.000)</td>
<td></td>
<td>-0.213 (0.081)</td>
<td></td>
<td></td>
<td>-0.446 (0.045)</td>
<td>-0.147 (0.038)</td>
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<tr>
<td>Openness</td>
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<td>0.397 (0.000)</td>
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<tr>
<td>Deregulation</td>
<td></td>
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<td></td>
<td>0.038 (0.000)</td>
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<tr>
<td>Weather</td>
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<tr>
<td>Time</td>
<td>0.016 (0.000)</td>
<td>0.006 (0.080)</td>
<td>0.032 (0.000)</td>
<td>0.040 (0.000)</td>
<td>-0.032 (0.000)</td>
<td>-0.022 (0.000)</td>
<td>0.007 (0.242)</td>
<td>-0.017 (0.000)</td>
<td>0.017 (0.007)</td>
<td>0.013 (0.000)</td>
<td>-0.018 (0.000)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.498 (0.002)</td>
<td>2.455 (0.000)</td>
<td>4.005 (0.000)</td>
<td>1.855 (0.004)</td>
<td>0.068 (0.000)</td>
<td>5.465 (0.000)</td>
<td>4.314 (0.000)</td>
<td>4.694 (0.000)</td>
<td>13.133 (0.000)</td>
<td>8.806 (0.000)</td>
<td>1.064 (0.112)</td>
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<tr>
<td>$R^2$</td>
<td>0.996</td>
<td>0.673</td>
<td>0.996</td>
<td>0.991</td>
<td>0.822</td>
<td>0.601</td>
<td>0.774</td>
<td>0.977</td>
<td>0.887</td>
<td>0.973</td>
<td>0.982</td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>1.661</td>
<td>0.553</td>
<td>1.436</td>
<td>0.820</td>
<td>0.654</td>
<td>1.005</td>
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<td>2.019</td>
<td>1.061</td>
<td>2.177</td>
<td>1.791</td>
</tr>
<tr>
<td>White heteroskedasticity</td>
<td>(0.116)</td>
<td>(0.007)</td>
<td>(0.62)</td>
<td>(0.075)</td>
<td>(0.014)</td>
<td>(0.344)</td>
<td>(0.336)</td>
<td>(0.127)</td>
<td>(0.059)</td>
<td>(0.079)</td>
<td>(0.167)</td>
</tr>
<tr>
<td>Jarque-Bera normality</td>
<td>(0.813)</td>
<td>(0.925)</td>
<td>(0.830)</td>
<td>(0.581)</td>
<td>(0.989)</td>
<td>(0.881)</td>
<td>(0.069)</td>
<td>(0.734)</td>
<td>(0.797)</td>
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</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
### Table 3: Results for equation (10)

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<thead>
<tr>
<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics, computers &amp; software capital</td>
<td>0.033</td>
<td>-0.346</td>
<td>0.194</td>
<td>-0.281</td>
<td>-0.043</td>
<td>-0.188</td>
<td>0.453</td>
<td>0.113</td>
<td>-0.388</td>
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<tr>
<td></td>
<td>(0.079)</td>
<td>(0.073)</td>
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<td>(0.086)</td>
<td>(0.000)</td>
<td>(0.001)</td>
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<tr>
<td>Other capital</td>
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<td>0.773</td>
<td>0.700</td>
<td>0.912</td>
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<td>(0.091)</td>
<td>(0.075)</td>
<td>(0.016)</td>
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<td>(0.000)</td>
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<td>0.007</td>
<td>0.019</td>
<td>0.026</td>
<td>0.014</td>
<td>0.017</td>
<td>-0.026</td>
<td>0.025</td>
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<td>(0.000)</td>
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<td>(0.005)</td>
<td>(0.185)</td>
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<td>Constant</td>
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<td>(0.016)</td>
<td>(0.023)</td>
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<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.000)</td>
<td>(0.054)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.992</td>
<td>0.979</td>
<td>0.998</td>
<td>0.997</td>
<td>0.966</td>
<td>0.975</td>
<td>0.860</td>
<td>0.998</td>
<td>0.983</td>
<td>0.988</td>
<td>0.996</td>
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<tr>
<td>Durbin-Watson</td>
<td>1.287</td>
<td>0.545</td>
<td>1.489</td>
<td>0.982</td>
<td>0.309</td>
<td>1.277</td>
<td>2.249</td>
<td>2.145</td>
<td>1.597</td>
<td>1.963</td>
<td>1.695</td>
</tr>
<tr>
<td>White heteroskedasticity</td>
<td>(0.352)</td>
<td>(0.056)</td>
<td>(0.746)</td>
<td>(0.026)</td>
<td>(0.062)</td>
<td>(0.227)</td>
<td>(0.261)</td>
<td>(0.164)</td>
<td>(0.508)</td>
<td>(0.088)</td>
<td>(0.382)</td>
</tr>
<tr>
<td>Jarque-Bera normality</td>
<td>(0.928)</td>
<td>(0.645)</td>
<td>(0.744)</td>
<td>(0.456)</td>
<td>(0.583)</td>
<td>(0.964)</td>
<td>(0.105)</td>
<td>(0.514)</td>
<td>(0.486)</td>
<td>(0.671)</td>
<td>(0.631)</td>
</tr>
</tbody>
</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
Table 4: $\hat{\theta}$ from equation (9) and testing for excess returns

<table>
<thead>
<tr>
<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Market sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0: \theta = 5$</td>
<td>(0.000)</td>
<td>(0.033)</td>
<td>(0.170)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.021)</td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.063)</td>
<td>(0.152)</td>
</tr>
<tr>
<td>$H_0: \theta = 12$</td>
<td>(0.000)</td>
<td>(0.500)</td>
<td>(0.017)</td>
<td>(0.002)</td>
<td>(0.117)</td>
<td>(0.887)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Computers</td>
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<td>-65.162</td>
<td>0.755</td>
<td>-17.700</td>
<td>33.653</td>
<td>28.545</td>
<td>88.449</td>
<td>6.114</td>
<td>61.438</td>
<td>-0.838</td>
<td>12.457</td>
</tr>
<tr>
<td>$H_0: \theta = 12$</td>
<td>(0.000)</td>
<td>(0.266)</td>
<td>(0.046)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.012)</td>
<td>(0.001)</td>
<td>(0.004)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.824)</td>
</tr>
</tbody>
</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
Table B1: Results for equation (9), estimated in differences

<table>
<thead>
<tr>
<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and Insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Market sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Electronics, computers &amp; software) / capital (KH/K)</td>
<td>-1.352 (0.153)</td>
<td>-29.937 (0.013)</td>
<td>-1.648 (0.319)</td>
<td>-7.432 (0.000)</td>
<td>2.149 (0.204)</td>
<td>3.351 (0.238)</td>
<td>-16.540 (0.501)</td>
<td>1.144 (0.365)</td>
<td>9.359 (0.015)</td>
<td>1.104 (0.563)</td>
<td>1.355 (0.401)</td>
</tr>
<tr>
<td>R&amp;D</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business cycle</td>
<td>0.040 (0.034)</td>
<td>0.055 (0.084)</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.048 (0.018)</td>
</tr>
<tr>
<td>Energy prices</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Terms of trade</td>
<td>0.272 (0.030)</td>
<td>0.187 (0.03)</td>
<td>0.284 (0.004)</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Deregulation</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weather</td>
<td>0.036 (0.001)</td>
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<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>Constant</td>
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<td>0.037 (0.000)</td>
<td>0.037 (0.000)</td>
<td>0.005 (0.444)</td>
<td>-0.008 (0.294)</td>
<td>0.026 (0.206)</td>
<td>-0.020 (0.033)</td>
<td>0.041 (0.085)</td>
<td>0.022 (0.010)</td>
<td>0.010 (0.046)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>-0.007</td>
<td>0.135</td>
<td>-0.016</td>
<td>0.359</td>
<td>0.112</td>
<td>0.076</td>
<td>0.101</td>
<td>0.296</td>
<td>0.237</td>
<td>0.022</td>
<td>0.269</td>
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<tr>
<td>Durbin-Watson</td>
<td>2.303</td>
<td>2.082</td>
<td>2.227</td>
<td>1.874</td>
<td>1.400</td>
<td>2.345</td>
<td>3.004</td>
<td>1.967</td>
<td>2.144</td>
<td>2.770</td>
<td>2.209</td>
</tr>
<tr>
<td>White heteroskedasticity</td>
<td>(0.851)</td>
<td>(0.416)</td>
<td>(0.752)</td>
<td>(0.883)</td>
<td>(0.995)</td>
<td>(0.001)</td>
<td>(0.091)</td>
<td>(0.400)</td>
<td>(0.789)</td>
<td>(0.742)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>Jarque-Bera normality</td>
<td>(0.366)</td>
<td>(0.083)</td>
<td>(0.002)</td>
<td>(0.570)</td>
<td>(0.795)</td>
<td>(0.001)</td>
<td>(0.392)</td>
<td>(0.587)</td>
<td>(0.774)</td>
<td>(0.612)</td>
<td>(0.540)</td>
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</tbody>
</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
Table B2: Results for equation (10), estimated in differences

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<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Market sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronics, computers &amp; software capital</td>
<td>-0.027 (0.43)</td>
<td>-0.388 (0.043)</td>
<td>0.114 (0.219)</td>
<td>-0.203 (0.006)</td>
<td>0.095 (0.483)</td>
<td>0.079 (0.68)</td>
<td>-0.493 (0.468)</td>
<td>0.133 (0.102)</td>
<td>-0.072 (0.648)</td>
<td>0.142 (0.115)</td>
<td>0.026 (0.817)</td>
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<tr>
<td>Other capital</td>
<td>0.393 (0.009)</td>
<td>1.190 (0.000)</td>
<td>0.791 (0.000)</td>
<td>1.212 (0.000)</td>
<td>0.641 (0.000)</td>
<td>0.340 (0.036)</td>
<td>1.920 (0.022)</td>
<td>0.068 (0.656)</td>
<td>0.635 (0.047)</td>
<td>0.632 (0.003)</td>
<td>0.399 (0.055)</td>
</tr>
<tr>
<td>Labour</td>
<td>0.634 (0.000)</td>
<td>0.198 (0.080)</td>
<td>0.095 (0.491)</td>
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<td>0.264 (0.178)</td>
<td>0.581 (0.000)</td>
<td>-0.427 (0.624)</td>
<td>0.798 (0.000)</td>
<td>0.437 (0.04)</td>
<td>0.226 (0.203)</td>
<td>0.219 (0.018)</td>
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<td>0.356 (0.048)</td>
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<tr>
<td>Energy prices</td>
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<td>-0.063 (0.009)</td>
</tr>
<tr>
<td>Terms of trade</td>
<td>0.239 (0.057)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.208 (0.026)</td>
</tr>
<tr>
<td>Weather</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.004 (0.131)</td>
</tr>
<tr>
<td>Openness</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.363 (0.000)</td>
</tr>
<tr>
<td>Deregulation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.024 (0.000)</td>
<td>-0.004 (0.828)</td>
<td>0.019 (0.030)</td>
<td>0.023 (0.000)</td>
<td>0.000 (0.989)</td>
<td>-0.003 (0.830)</td>
<td>0.021 (0.414)</td>
<td>0.040 (0.015)</td>
<td>0.027 (0.123)</td>
<td>0.018 (0.253)</td>
<td>-0.010 (0.332)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.626</td>
<td>0.070</td>
<td>0.061</td>
<td>0.507</td>
<td>0.234</td>
<td>0.468</td>
<td>0.107</td>
<td>0.571</td>
<td>-0.167</td>
<td>-1.209</td>
<td>0.633</td>
</tr>
<tr>
<td>Durbin-Watson</td>
<td>2.275</td>
<td>1.757</td>
<td>2.035</td>
<td>1.342</td>
<td>1.355</td>
<td>2.329</td>
<td>2.899</td>
<td>2.132</td>
<td>1.782</td>
<td>1.958</td>
<td>1.969</td>
</tr>
<tr>
<td>White heteroskedasticity</td>
<td>(0.459)</td>
<td>(0.701)</td>
<td>(0.178)</td>
<td>(0.942)</td>
<td>(0.637)</td>
<td>(0.000)</td>
<td>(0.104)</td>
<td>(0.727)</td>
<td>(0.314)</td>
<td>(0.011)</td>
<td>(0.185)</td>
</tr>
<tr>
<td>Jarque-Bera normality</td>
<td>(0.670)</td>
<td>(0.265)</td>
<td>(0.016)</td>
<td>(0.852)</td>
<td>(0.616)</td>
<td>(0.004)</td>
<td>(0.812)</td>
<td>(0.735)</td>
<td>(0.840)</td>
<td>(0.504)</td>
<td>(0.982)</td>
</tr>
</tbody>
</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
Table B3: $\hat{\theta}$ from equation (9), estimated in differences, and testing for excess returns

<table>
<thead>
<tr>
<th>Market sector</th>
<th>Manufacturing</th>
<th>Mining</th>
<th>Transport, Storage and Communication</th>
<th>Electricity, Gas and Water</th>
<th>Wholesale and Retail trade</th>
<th>Construction</th>
<th>Agriculture</th>
<th>Finance and insurance</th>
<th>Accommodation, Cafes and Restaurants</th>
<th>Cultural and Recreational Services</th>
<th>Market sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0$: $\theta = 5$</td>
<td></td>
<td></td>
<td>(0.002)</td>
<td>(0.006)</td>
<td>(0.026)</td>
<td>(0.000)</td>
<td>(0.788)</td>
<td>(0.000)</td>
<td>(0.026)</td>
<td>(0.000)</td>
<td>(0.788)</td>
</tr>
<tr>
<td>$H_0$: $\theta = 12$</td>
<td></td>
<td></td>
<td>(0.066)</td>
<td>(0.146)</td>
<td>(0.011)</td>
<td>(0.000)</td>
<td>(0.820)</td>
<td>(0.000)</td>
<td>(0.011)</td>
<td>(0.000)</td>
<td>(0.820)</td>
</tr>
<tr>
<td>Computers</td>
<td>-5.638</td>
<td>-200.01</td>
<td>-17.814</td>
<td>-33.566</td>
<td>10.661</td>
<td>23.198</td>
<td>44.396</td>
<td>16.011</td>
<td>43.035</td>
<td>-2.373</td>
<td>7.132</td>
</tr>
<tr>
<td>$H_0$: $\theta = 12$</td>
<td></td>
<td></td>
<td>(0.020)</td>
<td>(0.010)</td>
<td>(0.002)</td>
<td>(0.000)</td>
<td>(0.574)</td>
<td>(0.119)</td>
<td>(0.309)</td>
<td>(0.147)</td>
<td>(0.040)</td>
</tr>
</tbody>
</table>

Note: numbers in brackets are p-values. The p-values on the coefficients are calculated using heteroskedasticity and autocorrelation robust Newey-West standard errors.
Figure 1

Multi-Factor Productivity
Annual log-levels, base 1975 = 100

Figure 2

Marginal Product of High-Tech Capital