PRODUCTIVITY COMMISSION

The Increasing Demand for Skilled Workers in Australia: The Role of Technical Change

Staff Research Paper

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The views expressed in this paper are those of the staff involved and do not necessarily reflect those of the Productivity Commission. Appropriate citation in indicated overleaf.

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Abbreviations and explanations

Abbreviations

ABS	Australian Bureau of Statistics
ANZSIC	Australia and New Zealand Standard Industrial Classification
ASCO1	Australian Standard Classification of Occupations, first edition
ASCO2	Australian Standard Classification of Occupations, second edition
ASIC	Australian Standard Industrial Classification
AWE	average weekly earnings
B&S	buildings and structures
BERD	business expenditure on research and development
CCLO	Classification and Classified List of Occupations
ETM	elaborately transformed manufactures
IC	Industry Commission
LFS	Labour Force Survey
M&E	machinery and equipment
OECD	Organisation for Economic Co-operation and Development
R&D	Research and development
SBTC	skill biased technological change
SUR	seemingly unrelated regressions

Explanations

Data terminology

Term	*Definition*
Industry division data	Data assembled at the ANZSIC 1-digit industry division level.
Manufacturing data	Data assembled at the ANZSIC 2 digit manufacturing subdivision level.
Skill intensity	The percentage of high skilled workers in total employment or the total wage bill.
Skill upgrading	An increase in skill intensity. Also referred to as upskilling.
Deskilling	A decrease in skill intensity.

Definition of sectors and industries[a]

Sector	*ANZSIC industry division data*
Primary	Agriculture, forestry and fishing
	Mining
Manufacturing	Manufacturing
Utilities and construction	Electricity, gas and water supply
	Construction
Services	Wholesale trade
	Retail trade
	Accommodation, cafes and restaurants
	Transport and storage
	Communication services
	Finance, property and business services
	Government administration and defense
	Education, health and community services
	Cultural and recreational services
	Personal and other services

Sector	*ANZSIC manufacturing data*
Manufacturing	Food, beverages and tobacco
	Textiles, clothing, footwear and leather
	Printing, publishing and recorded media
	Petroleum, coal, chemicals and associated products
	Basic metal products
	Fabricated metal products
	Transport equipment
	Other manufacturing

Definition of occupational groups

Occupation group	*ASCO1 major occupation group*
High skilled workers	Managers and administrators
	Professionals
	Para-professionals
Other workers	Tradespersons
	Clerks
	Salespersons and personal service workers
	Plant and machine operators and drivers
	Labourers and related workers

a See appendix A for a detailed explanation of data sources and concordances.

Key findings

- Since 1978, the proportion of skilled workers in total employment has increased significantly in Australia. This trend has been mirrored by an increase in their share of the total wage bill over the years for which data are available (1986 onward). These trends are evident in all but the primary sector.
- These changes are primarily due to the increase in the share of skilled workers (of both genders) across all industries — as opposed to one industry increasing its share at the expense of another. This pattern is consistent with changes due to technology more so than increases in international trade. That is not to say that trade cannot influence the manner and speed with which industries take-up new technologies.
- For the manufacturing sector, there is a strong positive association between technological change and the share of employment and the wage bill of skilled workers. This finding is consistent with the results of several overseas studies.
- A majority of industries show a relationship between technological change and the increased demand for skilled workers. This support, however, is not as strong as that found for the manufacturing sector by itself.
- This relationship appears to have strengthened since the mid-1980s, coinciding with a period of extensive microeconomic reform. Thus, recent deregulation may have assisted producers in adopting new technologies requiring skilled workers.
- The majority of industries show a positive association between the amount of software and machinery and equipment used and the share of skilled workers demanded.
- Adding trade to the analysis shows that, for the most part, imports do not influence the relative demand for skilled workers. However, exports are positively associated with the demand for skilled workers. This implies that increasing imports are not leading to a widespread change in the relative demand for workers. At the same time, exports appear to be spurring the demand for skilled workers.

Overview

This paper examines the changing demand for high skilled workers in Australia. It was undertaken in order to provide insights into possible causes of the changing earnings distribution in the country. There are two main arguments used to explain these trends. The first is that rising levels of imports from low wage countries will reduce the relative demand for low skilled workers. This is known as the trade hypothesis. The second argument is that technological change increases the demand for high skilled workers economywide as new technologies are biased towards this group of workers. As a result, technological changes over time would benefit the employment and wage prospects of high skilled workers relative to their lower skilled counterparts. This is known as the skill biased technical change (SBTC) hypothesis. The paper focuses on the SBTC hypothesis and its potential affect on the demand for high skilled workers.

Examining the changing share of high skilled workers in total employment shows that the bulk of this change is associated with a general increase within each industry, rather than changes between industries. In a broad sense, this supports SBTC as the theory states that technological change affects all industries' demand for skilled workers, rather than a select few. If the alternative explanation, the trade hypothesis, was supported there would be a shifting of workers between industries, as those affected adversely by trade would lose workers and others would gain. This is not the case. The dominance of the overall, or 'within-industry' affect is consistent with findings for other OECD countries (eg Berman et al. 1994).

The analysis covers the years 1978 through 1998. This time frame includes a period of extensive microeconomic reform in Australia. In order to determine if this reform period affected the results in any way, the same analysis was conducted over two subperiods, one corresponding to low levels of reform (1978-85) and one to high levels (1986-98). The within-industry affects are stronger in the high reform period. This suggests that microeconomic reform could have influenced the employment-technology link in Australia.

The findings in support of SBTC remain consistent when possible gender specific influences are examined. The within-industry effects between 1978 and 1998 show a general skill upgrading in the economy rather than job composition changes or gender specific upskilling. This is in spite of the increased labour force participation of females and their overrepresentation in lower skilled occupations.

The analysis so far is based on broad trends and thus does not provide clear support for SBTC. First, openness to international trade may encourage any domestic technology-driven skill upgrading already taking place. Second, between-industry effects may also result from SBTC, as some industries adopt new technologies faster than others. Therefore, more in-depth analysis is applied through regression techniques.

To measure technological change, R&D per unit of output (referred to as R&D intensity) is used. However, the installation of new capital equipment may also be due to technological change. More sophisticated equipment may call for an increase the number of high skilled workers employed in an industry. The increase in demand for skilled workers due too more advanced capital equipment is known as capital-skill complementarity. Thus, SBTC is investigated through both a measure of technical change, R&D intensity, and the complementary relationship between capital and high skilled workers.

Overall, the findings from the regression work support SBTC. The equations using wage bill shares produce stronger results than those using employment shares. Also, the results for individual manufacturing industries are more persuasive than for all industries economywide.

Evidence of capital-skill complementarity is found in manufacturing. For the industries where information is available on software assets, it is found that the more computer-intensive an industry, the more likely it is (on average) to employ high skilled workers. Machinery and equipment does not appear as strong an influence across all industries economywide. However, this may be a reflection of the fact that the degree to which technological advances can be found in machinery and equipment differs between industries.

When trade variables are included, there is a consistent and positive association between exports and skilled workers. Such a firm relationship was not found with imports, however. With import competition affecting more than 85 per cent of Australia's manufacturing output, support for the trade hypothesis should have been detected via imports in manufacturing. Yet, in most cases no such evidence was found. The fact that exports were found to be an important influence on the relative share of high skilled workers and imports were not suggests that openness to international trade has not resulted in widespread losses of low skilled jobs.

Looking at periods of low and high microeconomic reform supports the argument that reform has had an influence on the demand for high skilled workers in the economy. Both in manufacturing and economywide, most of the results are concentrated in the high reform period. This can be seen as evidence that through reform, businesses are able to re-examine and optimise their choices in using different inputs available to them — such as labour and capital.

1 Introduction

1.1 Rationale for the study

Although there has been considerable growth in the real average earnings of employees in Australia since the mid-1970s, it has not been evenly distributed.[1] For example, real weekly earnings for males in the lowest and highest income deciles grew by 0.5 per cent and 28.5 per cent respectively between 1975 and 1998 (table 1.1). Earnings (wages and salaries) account for approximately 70 per cent of household income. Therefore what happens to earnings strongly influences the welfare of Australians. For this reason, there is concern over the increase in the dispersion of earnings over the past two decades.

Table 1.1 **Change in Australian real weekly earnings, 1975 to 1998**

	Lower decile	*Lower quintile*	*Median*	*Upper quintile*	*Upper decile*
Males	0.5	7.7	17.0	22.9	28.5
Females	11.5	16.8	25.0	38.0	38.0

Source: Norris and McLean 1999.

There are numerous studies of the Australian economy which have underlined this increasing dispersion in earnings between groups of workers. For example, Pappas (2000) outlines evidence of growing inequality across different skill levels between 1986 and 1996, driven largely by growth in weekly wage inequalities. This work supports earlier findings by Saunders (1995), Borland and Wilkins (1996), Borland (1998) and Harding and Richardson (1998).

Borland (1998) suggests that an increase in earnings dispersion may increase the need for government transfers and reduce incentives to job search. Furthermore, he notes the possibility that earnings inequality may be self-perpetuating if children of parents with low earnings are not able to acquire sufficient skills to obtain satisfactory employment.

1 This trend has also been documented in many other OECD countries. See, for example, Gregg and Machin (1994) for the UK, Bound and Johnson (1992) for the US, and Davis (1992) and OECD (1993) for international comparisons.

However, the link between earnings inequality and skill acquisition may also work the other way. Under this scenario, greater dispersion and increased returns to skills create incentives to acquire skills so that, in the future, the number of high skilled workers will increase and earnings distribution will become relatively more equal (as the high skilled wage premium decreases).

In a broad sense, the changing earnings distribution affects perceptions of fairness and equity within the community. An example is the popular view that the microeconomic reforms of the past two decades have affected some groups of workers disproportionately. Commonly cited examples include the perceived impact of tariff reductions and industrial relations reform on the wages and employment prospects of lower skilled workers relative to those of other workers.

The widening of the earnings distribution is related to changes in the labour market. As shown in table 1.1, the growth in real weekly earnings for females in the upper decile of the distribution, for example, was more than three times the growth in earnings experienced by females in the lower decile. This outcome is consistent with an increase in the supply of workers in the lower deciles, relative to demand, having a dampening effect on wages. It is also consistent with an increase in the demand for workers in the higher deciles, relative to supply, pulling wages up. Although supply side factors are important, this paper will focus on demand factors which many think are the main reason for the growing earnings dispersion in Australia since the mid-1980s (Borland 1998).

For policy purposes, a better understanding of the relationships between trends in earnings distribution, labour markets and policy is needed. Earnings distribution is a reflection of labour market outcomes. These outcomes are a function of the labour markets — that is, the relative supply and demand for different types of labour and the environment in which they operate.

1.2 Labour market environment

The ability of the labour market to adjust to a changing environment affects the supply of workers, the demand for workers and the wages they are paid. Thus labour market flexibility influences the earnings and employment patterns in an economy. The changing earnings distribution in Australia needs to be understood in the context of its labour market flexibility. Undertaking an examination of earnings outcomes then requires an understanding of these underlying market characteristics.

Labour market flexibility is influenced by factors on both the demand and supply side. Demand side factors include businesses needing to hire suitable workers and achieving the most efficient resource mix. This is vital for industry to compete successfully in an open economy. Labour supply involves workers with the appropriate skills, and the ability to move to where demand is. An inability of supply to keep pace with demand may create 'bottlenecks' in the system.

The observed change in earnings distribution in the Australian economy, all other things being equal, implies that the demand for high skilled workers has outpaced the supply of such workers. Any change or shock to the demand for a particular type of labour (for example, high skilled workers) may alter the market in three distinctive ways:

- if the labour market is flexible, an increase in the dispersion of labour earnings will occur, in favour of workers experiencing higher productivity. In other words, the high skilled/lower skilled wage differential widens;
- if the labour market is rigid, the consequence is not so much an increase in the skill wage differential as an increase in the unemployment differential between skill levels, especially long-term unemployment;[2] and
- if the supply of skills which are in greater demand increases, neither the wage nor the unemployment differential need increase.

In the literature, all three outcomes have been reported at different times and for different countries. First, there is a general consensus that, faced with the same change in demand for high skilled workers (regardless of its cause), different countries responded differently. In the US and the UK, wage differentials widened. In most European countries, unemployment differentials widened (Colecchia and Papaconstantinou 1996, Pappas 1998). The difference is generally ascribed to the fact that the former countries have relatively flexible labour markets in comparison with the latter group (Mortensen and Pissarides 1999).

Second, it is often mentioned that a significant increase in the supply of graduates has at times helped keep the wage differential constant, for example in the US during the 1970s (Johnson 1997) and in Australia from the 1970s to the 1990s (Vickery 1999).

There is a consensus that the Australian labour market is relatively rigid (Sloan 1992, Pappas 1998, Dawkins and Kenyon 1999). This would imply that changes to labour demand are primarily reflected in an increase in unemployment differentials between groups of workers. Indeed, according to Vickery (1999) and supported in the findings presented here, the wage differential has not increased significantly since the mid-1980s. Vickery further contends that the increase in the long-term unemployment of lower skilled workers is not due to a shift in demand towards high

[2] A widening of the differential in labour force participation between skilled and unskilled persons is also likely in these circumstances.

skilled workers. Rather, he argues that unemployment of both high skilled and lower skilled workers has moved in similar fashion in response to aggregate (ie macroeconomic) wage shocks.

Pappas (1998), however, provides a more detailed analysis of long-term unemployment by skill level, revealing that it has grown relatively faster for motor skills (primarily blue collar) than for interactive skills (primarily white collar). Changes over time in skill-weighted indexes of the number of long-term unemployed persons are consistent with insufficient adjustment to an increase (decrease) in demand for interactive (motor) skill producing an increase in the number of long-term unemployed persons.

The picture emerging from a detailed look at Australia's labour markets is therefore one of increasing unemployment differentials by skill level. This is consistent with the depiction of Australia as a relatively rigid labour market. However, there is conflicting evidence on relative wage disparity, depending on the level of aggregation in the data. The more aggregate evidence shows limited growth in the earnings differential between high skilled and lower skilled workers. This finding is also consistent with countervailing shifts in supply.

What is clear from previous research, and supported in this paper, is that high skilled workers account for a greater share of both employment and earnings (as measured by the wage bill). This fact has led to concerns about the prospects of lower skilled workers in the economy.

1.3 Paper outline

Before a policy course can be decided upon, further understanding of the nature and causes of the increasing earnings dispersion is needed. This paper adds to the growing body of research on changing earnings distribution in Australia by providing insights into the factors influencing shifts in demand for skilled workers. The paper is organised as follows. Chapter 2 presents competing theories and documents trends in the skill composition of employment and wages in Australia since the late 1970s. Chapter 3 discusses methodology and data issues. A decomposition of the change in the share of high skilled workers is presented in chapter 4. Chapter 5 examines the relationship between technological change and the demand for high skilled workers, using econometric analysis. Chapter 6 summarises the conclusions arising from this research.

2 Theory and trends

This chapter provides a discussion of the theoretical issues behind the changes in earnings distribution and examines relevant economic trends in Australia between 1978 and 1998. Changes in the skill composition of employment and wages and the possible sources of those changes are reviewed.

2.1 Theoretical background

As stated in the Overview, the two main candidates identified in the literature to explain the shift in demand towards high skilled workers are rising levels of international trade and skill biased technological change (SBTC).

The trade hypothesis is part of a standard international trade theory, as represented by the Heckscher-Ohlin model (HO) and the Stolper-Samuelson Theorem (SS). Together, they provide an explanation for the possible effects of international trade on the demand for different types of labour, their remuneration and the intensity with which they are used. HO and SS predict that greater trade openness will increase the incentive (through relative price changes) of domestic producers to specialise in the production of goods that are intensive in their use of the relatively abundant factor of production. Assuming that high skilled workers are relatively abundant in Australia, this would mean an increase in the economywide demand for these workers and a decrease in the demand for other workers. As a result, wages of high skilled workers would increase relative to those of lower skilled workers.[1] This, in turn, would cause domestic producers to replace some high skilled workers with lower skilled workers in all industries in which substitution can occur. Thus, the trade hypothesis predicts that economywide increases in the share of high skilled workers will be the result of employment relocating from lower skilled intensive to high skilled intensive industries. Moreover, for given overall supplies of lower skilled and high skilled workers, the ratio of lower to high skilled workers in industries will rise, balanced overall by an increase in the size of high skilled industries.

[1] Abstracting from changes in the supply of different types of labour.

By contrast, the emphasis of the SBTC hypothesis is on changes taking place within industries. If technological change is biased toward high skilled workers, their productivity will increase, relative to that of other workers. Profit maximising producers will respond to this by altering their skill mix in favour of high skilled workers. If SBTC occurs, economywide demand for high skilled workers will increase, causing their relative wages to rise. Under this hypothesis, no interindustry reallocation of labour need occur for the economywide share of high skilled workers to increase.

A paper by the Industry Commission (IC), *Trade Liberalisation and Earnings Distribution in Australia* (Murtough et al. 1998), found that the growing dispersion of earnings is not significantly attributable to the reduction in trade barriers by Australia. Instead, the employment (and earnings) effects of lower trade barriers were overshadowed by other developments, including technological change that favoured a greater use of high skilled workers. These results are consistent with those obtained by Gaston (1998) for the manufacturing sector. This suggests that government assistance to those industries affected by the removal of protection is unlikely to change employment and earnings patterns in Australia significantly.[2] Similarly, little supporting evidence has been found for the trade hypothesis in other OECD countries.[3]

There has been considerable research testing the SBTC hypothesis for many OECD countries, especially in relation to manufacturing industries. This research provides evidence that technological change, by increasing the relative demand for high skilled labour, is the major explanatory factor of growing earnings dispersion within the manufacturing sector of the countries examined.

As with overseas studies, the limited empirical research on SBTC for Australia has largely centred on manufacturing (for example Borland and Foo 1996) — ‘limited’ because it has relied principally on decomposition analysis which represents only a preliminary attempt at measuring the effects of SBTC on the Australian economy. When multivariate regression analysis has been used, and the coverage broadened to the entire non-farm economy, data limitations have restricted the analysis to a cross-sectional approach (Pappas 1998).

Possibly as a consequence of the limitations outlined above, Vickery (1999) stated recently that ‘not enough evidence exists for Australia to make definitive statements about the causes of the demand shift [toward skilled labour]’ (p. 26). This paper

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2 Indeed other studies suggest that there is inadequate evidence to draw definitive conclusions about the link between changes in trade and the demand for high skilled workers (EPAC 1996).

3 See, for example, Machin and Van Reenen (1998), Haskel and Heden (1999) and Arego and Whalley (2000).

seeks to redress this lack of evidence by building on earlier analyses. In particular, it uses a comprehensive time series–cross section dataset to investigate the occurrence of skill biased technological change across all sectors of the economy over the period 1978–98. The lengthening and broadening of the coverage should allow the links between skill intensity, technology and economic structure to be better captured.

Before proceeding, two caveats are in order. First, the distinction between trade and technological change effects is a convenient, but not completely accurate, one. The two explanations could very plausibly be linked. On the one hand, increased pressure from international competition could cause producers to adopt more technology-intensive production methods within the same industry (Haskel 1996) or in other sectors of the economy (Machin and Van Reenen 1998). On the other hand, technology can stimulate trade; Dixon et al. (2000) use a CGE modelling framework to show that technical change in such inputs as communication equipment, communication services, scientific equipment and computers was a strong driver of import and export growth in Australia between 1987 and 1994.

A second caveat concerns the type of earnings inequality examined in this paper. As mentioned, increased earnings inequality between observable measures of skill, such as occupation and education, has been detected in Australia and elsewhere. However, earnings inequality can also happen with respect to *unobservable* characteristics. One such characteristic is natural ability. If the returns to unobserved ability are increasing, one would note a greater dispersion of earnings *within* groups of individuals with the same observable characteristics (for example female managers with a degree and 20 years of labour market experience). Indeed, this is what seems to be occurring, and studies have shown that it is a major driver of earnings inequality on the whole (see, for example, Borland 1998). Although an increase in returns to ability may also be due to technology, measures of such returns are readily available and are not considered in this paper.[4]

This paper concentrates on filling the gap in empirical knowledge that now exists regarding the relevance of the SBTC hypothesis for the increase in earnings dispersion by skill level in Australia. This goal implies a focus on the link between technological change and the demand for skilled workers in furthering understanding of the factors leading to greater earnings dispersion.

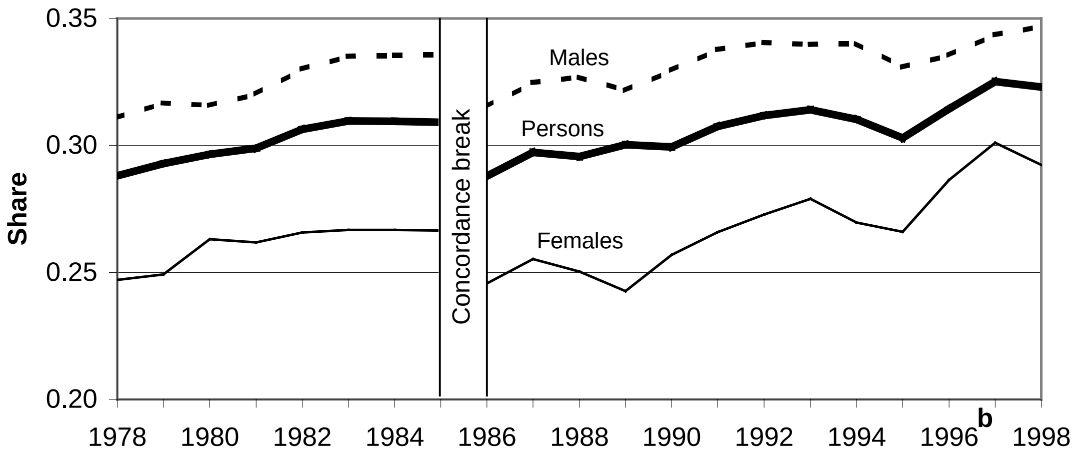
[4] Technically, worker ability should be controlled for in explaining the demand for skilled labour. However, this is not feasible with the data currently available.

2.2 The shift towards high skilled employment

Evidence of an increase in the share in employment of high skilled workers in Australia, or skill upgrading, is presented in figure 2.1. The share of high skilled employment increased by around 7 per cent between 1978 and 1985, and by around 12 per cent between 1986 and 1998. While a greater proportion of males than females is employed in high skilled occupations, the female share increased at almost double the rate of males from 1986 onward (19 per cent compared with 10 per cent).

Figure 2.1 **High skilled employment share in total employment by gender, 1978 to 1998[a]**

All industries



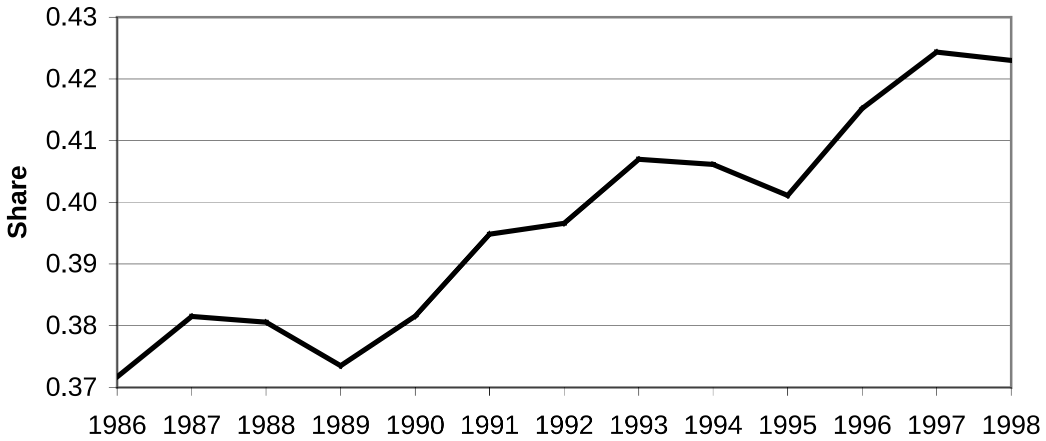
a Employment data are for August of each year. There were changes in the ABS occupational classifications in both 1986 and 1996 (see appendix A for details). **b** The change of classification which occurred in 1996 is minor and does not create a significant break in the employment series.

Source: Unpublished ABS Labour Force Survey data.

An alternative measure of skill upgrading is the change in the wage bill share of high skilled workers (figure 2.2). This is a more accurate measure than changes in employment shares as it is more likely to reflect occupational upgrading within broad classifications of skill — for example, para-professionals becoming managers. This phenomenon will be reflected in the wage bill share of high skilled workers, assuming wages rise when a worker moves to a higher skilled occupation.

As with employment shares, there is a clear upward trend in the wage bill share of high skilled workers between 1986 and 1998 (wage by occupation data are only available from 1986). As expected, high skilled workers consistently accounted for a greater share of the wage bill than of total employment over the period examined (figures 2.1 and 2.2). Moreover, the increase was larger for the wage bill share (14 per cent) than for the employment share (12 per cent) over this period.

Figure 2.2 **High skilled workers' share in the total wage bill, 1986 to 1998[a]**
All industries



a Wage bill by occupation and gender data are not collected for this study.
Source: Unpublished *ABS Employee Earnings and Hours Survey* data.

This suggests that the wage differential between high skilled and 'other' workers has increased.[5] However, as can be inferred from figure 2.3, this increase has been relatively modest — approximately 4 percentage points — from 1986 to 1998. These employment and wage trends support the contention that the Australian labour market is relatively rigid or inflexible compared with other OECD countries (see, for example, Pappas 1998 and Dawkins and Kenyon 1999). Holding other factors constant, this rigidity implies that a shift in demand towards skilled workers increases the employment differential between skill groups more than the wage differential.

The discrepancy between wage and employment outcomes has been observed in other OECD countries (see Berman et al. 1994, Machin et al. 1996 and Machin and Van Reenen 1998). For example, Machin et al. (1996, p. 2) found that in the US unemployment remained relatively stable while wage dispersion increased. By contrast, both wage dispersion and unemployment increased in the UK and remained relatively stable in Sweden. These inconsistencies may be partly related to the differences in labour market institutions in these countries.

5 Other workers consists of all remaining ASCO1 occupation groups, after removing high skilled workers.

Figure 2.3 **Average weekly total earnings of high skilled and other employees, 1986 and 1998[a]**

Current dollars

[a] Average weekly earnings for each group are constructed using employment-weighted averages.

Source: Unpublished ABS Employee Earnings and Hours Survey data.

2.3 Possible explanations for the shift towards high skilled employment

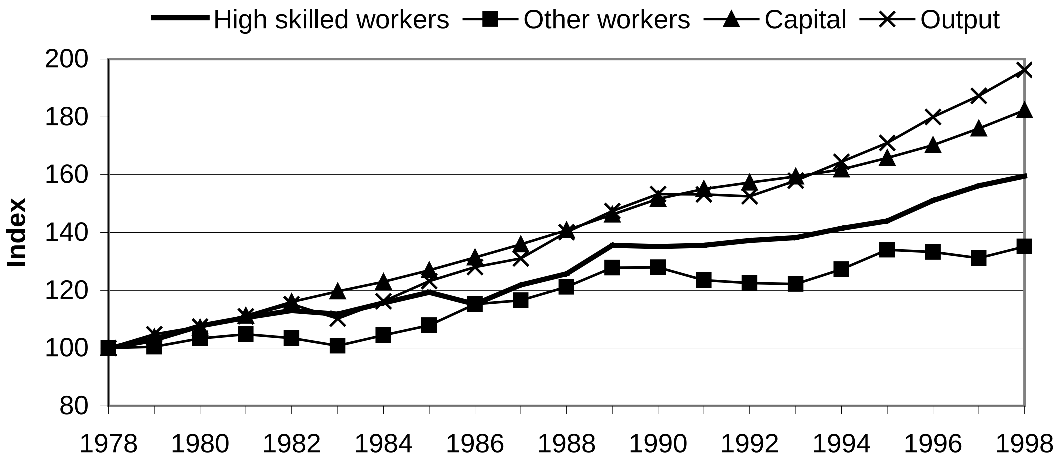
At the aggregate level, a comparison of trends in employment, output and capital highlights changes in the capital/labour relationship over time. Since new capital embodies a certain amount of innovation, these trends also shed some light on the rate of technological change in the economy.

Economywide trends in output and inputs

Figure 2.4 shows that output growth outstripped capital and employment growth between 1978 and 1998. These trends provide broad evidence of technological change — as fewer capital and labour inputs are required to produce a given level of output, all else held constant. Furthermore, the higher rates of growth for capital and output relative to employment suggest most of this is attributable to labour-saving technological change. However, the greater growth in the employment of high skilled workers compared to other workers suggests a complementary relationship between high skilled workers and physical capital.

Figure 2.4 **Output and input trends across all industries, 1978 to 1998[a]**

Index, 1978=100, capital and output at constant prices



[a] Employment series are affected by the changes of classification noted in relation to figure 2.1 and should be interpreted with caution.

Source: Commission estimates based on ABS data detailed in appendix A.

Technology and trade

As discussed, demand side explanations suggest that either rising international trade or SBTC or both are the major drivers of the changes observed above. While this paper focuses on the role of technological change, it is put into context by a discussion of trends in trade over the past two decades.

Trade

There has been a dramatic increase in the level of international trade between 1978 and 1998 (table 2.1).[6] Over this period, both imports and exports as a share of value added almost doubled. A trade-induced reallocation of employment between importing (traditionally lower skilled worker intensive) and exporting industries (traditionally high skilled worker intensive) would increase the overall share of high skilled workers in the economy. This would be consistent with the trade hypothesis.

6 This period was characterised by significant reductions in industry assistance, especially in the passenger motor vehicles and textiles, clothing and footwear industries (PC 1999). Both industries have traditionally had a relatively low share of high skilled employment.

Table 2.1 **Technology and trade indicators, 1978 to 1998**

	1978	*1988*	*1998*
Research and development			
Business expenditure on R&D (BERD) as a percentage of value added	0.26	0.51	0.82
BERD plus privately funded higher education R&D as a percentage of valued added	0.43	0.71	0.92
Capital Stock			
Net capital stock ($b)	459	647	838
Machinery and equipment as a percentage of net capital stock	27	30	31
Building and structures as a percentage of net capital stock	73	69	66
Software as a percentage of net capital stock	na	1	3
Computer use			
Share of businesses with computers (per cent)	na	49[a]	63
Computer users as a percentage of total employment	na	30[a]	40
International trade			
Exports as a percentage of value added	16	19	28
Imports as a percentage of value added	16	18	30

a 1993-94 data.

Sources: Commission estimates based on ABS data detailed in appendix A and on ABS (*Business Use of Information Technology*, Cat. no. 8129.0).

However, empirical work for Australia suggests that international trade has had only a minor (if any) influence on the relative demand for skilled workers in Australia (Borland 1998, Murtough et al. 1998).

Technology

R&D intensity (the ratio of R&D to value added) is used as a proxy for measuring technological change.[7] The data show that there has been a substantial rise in R&D intensity in Australia over the last two decades (table 2.1). Business expenditure on R&D (BERD) as a share of GDP increased from 0.26 per cent in 1978 to 0.82 per cent in 1998. Similar patterns emerge when R&D undertaken by higher education institutions is added to BERD. The introduction of the R&D tax concession in 1985 may have done much to spur this growth.[8]

7 See section 3.2.2 for a discussion of different indicators of technical change.

8 The tax concession originally amounted to 150 per cent of R&D spending, which was lowered to 125 per cent in 1996. It is possible that the introduction of this concession led to an increase in the *reporting* of R&D expenditure, rather than an increase in expenditure itself.

Changes in the net capital stock are an indirect indicator of the diffusion of new technological knowledge in the economy.[9] While there has been considerable growth in the net capital stock (figure 2.4), its composition has changed somewhat over the last two decades. In particular, machinery and equipment and software as a share of net capital stock increased steadily between 1978 and 1998. In many cases, machinery and equipment and software require skilled operators for their use.

The extent of computer use is also commonly used as an indicator of technological change.[10] However, the ABS has only collected computer use data for the two years 1993-94 and 1997-98. Between these years, the proportion of those in employment using computers rose from around 30 per cent to 40 per cent (table 2.1). There was also strong growth in the share of businesses with computers — rising from around 50 per cent in 1993-94 to over 60 per cent in 1997-98.

2.4 Summary

This chapter has reviewed the two theories underlying the change in earnings distribution: the trade hypothesis and SBTC. Trends in employment, output, capital, technology indicators and international trade were then examined. As in other OECD countries, there has been a significant increase in the share of employment and wages of high skilled workers in Australia over the past two decades. This shift has coincided with a rise in indicators of technological change, such as R&D intensity and computer use. In addition, a complementary relationship between high skilled workers and physical capital appears to exist. Together, these trends are consistent with the SBTC hypothesis. However, the sharp rise in imports and exports raises the possibility that, contrary to most findings to date, trade may also be contributing to the rise in the demand for skilled workers.

9 This is because new capital may not necessarily involve new technologies. An obvious example is some building investments.

10 The impact of computerisation on the demand for skills depends on whether it complements or substitutes for skills. Generally speaking, computerisation reduces the demand for lower skilled workers and increases the demand for high skilled workers.

3 Methodology and data

3.1 Methodology

Building on the descriptive analysis made in chapter 2 of a concurrent increase in the share of high skilled workers and the use of technology since 1978, this chapter attempts to provide additional insights into the relationship between technological change and high skilled workers through the following strategy. First, a standard decomposition analysis is applied to the share of high skilled employment. This apportions the change in the share of skilled workers to shifts between industries and shifts within industries. That is, how much of the change in the proportion of high skilled workers is due to the reallocation of employment between industries rather than to each industry upskilling (ie using relatively more high skilled workers) within itself. The trade hypothesis predicts a reallocation of lower skilled/high skill workers between industries. Thus, a predominance of between industry effects would support the trade hypothesis. Given the spread of technological change across the economy, the SBTC hypothesis predicts that the majority of changes occur within industries.

Next, regression analysis is applied to further investigate the within industry upskilling trend. This method consists of the estimation of a model linking the demand for high skilled workers in an industry to a number of determinants. Typically, such a demand equation is derived from a cost function containing wages, output (or another indicator of scale such as capital stock) and environmental variables as its arguments. Given the functional form used in this project (see appendix C), the demand variable is represented by the share of high skilled workers in either total employment or the total wage bill. Given that the focus of this paper is on SBTC, technology–related environmental variables are of most interest. Accordingly, the main model used in the regressions seeks to investigate the existence of a correlation between the share of high skilled workers and various technological change indicators.

These technological change indicators pertain directly to the industry whose share of high skilled workers is being explained. This is because it is plausible to think that the prime determinant of an industry’s demand for skilled labour is the degree of technological change undergone by that industry. However, it is less clear that technological change undergone by an industry is the same as technological change *originating* in an industry. That is, an industry can benefit from technological breakthroughs achieved elsewhere in the economy. For that reason, it is desirable to avoid examining industries in isolation in the regression analysis.

Econometric techniques are available which allow industry–specific characteristics to be preserved while explicitly recognising the inter-industry technological linkages and spillovers that exist in a modern, open economy. Specifically, this paper uses two techniques — panel data analysis and Seemingly Unrelated Regressions (SUR) — to allow for this kind of interconnectedness. As explained further in chapter 5 and appendix C, these techniques have the added advantages of capturing the time as well as cross–sectional dimension of the data, and accounting for the heterogeneity (or lack thereof) of the data.

Including some further environmental variables — namely trade — into the analysis tests, following the estimation of the main model, the robustness of its findings. This variant is viewed as a more stringent test of any SBTC findings because the persistence of technological change effects in a trade–augmented model would only reinforce any SBTC conclusions drawn from the initial model. Alternatively, the dominance of trade effects over technological effects in the extended model would raise the possibility that trade effects are a significant — if not the main — factor of skill upgrading.

The final variant concerns microeconomic reform in Australia. It is designed to allow the model to take into account the potential effects of some government policies on the technological change–demand for skills relationship.

Microeconomic reforms such as privatisation, corporatisation and deregulation, by removing restrictions on production processes, may alter the incentives facing producers and allow them to respond better to price signals in product and factor markets. This could lead, among other things, to producers employing more technologically–advanced processes, or more highly skilled workers, or both. Put another way, there may be some interaction between microeconomic reform and the link between technological change and the demand for skills.

Microeconomic reform in Australia has not proceeded at a constant pace. While there were some important early steps, reforms grew in coverage and intensity from the mid-1980s onward (see box 3.2).[1] Thus, two subperiods may be distinguished: the first, from 1978 to 1985, was a period of low intensity reform ('low reform'

[1] The box is indicative of the type and timing of reforms rather than being comprehensive.

henceforth); and the second, from 1986 to 1998, was a period of high intensity reform ('high reform' henceforth).[2]

If, as hypothesised, there is a synergy between microeconomic reform and the technological change–skills link, it is more likely to be apparent during the high reform period. It is desirable, therefore, that the low and high reform periods be identified in the analysis, when examining the determinants of employment shares.[3] In the event that SBTC was found to have increased during the high reform period, this would provide policy makers with a deeper understanding of the effects of future reforms.

The approach adopted in this paper to distinguish between the high and low reform periods is to estimate the trade-augmented model for the two periods separately.[4] The extended model specification is chosen to capture the belief that a surge in exports and imports coincided with the high period of microeconomic reform (see chapter 5 for details).

3.2 Technological change or computers?

Technological change is not a new phenomenon. In one sense, the 1876–1886 decade may be regarded as having produced the greatest technological change ever, with the invention of electric light, the automobile, the telephone and vaccines (Bunch and Hellemans 1994). Accordingly, some authors have pointed out that the spread of new technologies greatly increased the relative demand for non-production workers and more educated production workers in manufacturing between 1909 and 1929 (Goldin and Katz 1998). They conclude that capital–skill complementarity was already large in the first half of the twentieth century. However, Autor et al. (1998) suggest that the relative demand for high skilled workers grew more rapidly during 1970–1996 than during the previous three decades. They further state that:

> The diffusion of computers and related technologies and changes in the organisation of work associated with effectively utilising these technologies may be sufficiently

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[2] Given that each of the two time periods experienced similar business cycles, differing macroeconomic environments will not be a factor in these results.

[3] Wage data are only available for 1986–1998, so that this hypothesis cannot be tested for the wage bill share.

[4] An alternative, which consists of flagging differing reform intensities through the use of dummy variables was discarded for two reasons: (i) an intercept dummy would have coincided with an existing dummy denoting the concordance break in the employment series; and (ii) slope dummies would have severely restricted the number of degrees of freedom available.

widespread to have contributed to this pattern of more rapid within-industry skill upgrading in recent years. (1998, p. 1172)

Box 3.1 Microeconomic reform in Australia

A series of microeconomic reforms have been implemented over the past two decades aimed at improving the productivity of the Australian economy, and ultimately the living standards of Australians. While there were some important early steps, reforms grew in coverage and intensity from the mid-1980s, as indicated by the table below.[a] The table is indicative of the type and timing of reforms rather than being comprehensive.

Selected microeconomic reforms in Australia since the 1970s

Year	*Reform description*	*Industries most directly affected*
1973	Across the board reduction in tariffs of 25 per cent	Manufacturing
1983	Australian dollar floated and barriers to movements of foreign capital and entry of foreign banks reduced	Finance, property and business services
1985	Introduction of the 150 per cent R&D tax concession	
1988	Tariff and quota reductions to be phased in over the next four years Ability to develop enterprise agreements first introduced	Manufacturing
1989	Greater corporatisation, privatisation, commercialisation and contracting out of government activities (including GBEs)	Electricity, gas and water; Government administration and defence
1990	Special Premiers Conference agrees to a national electricity market	Electricity, gas and water
1995	National Competition Policy Agreement	Electricity, gas and water; Transport and storage; Communication services
1996	Reduction of R&D tax concession to 125 per cent	
1997	Introduction of Workplace Relations Act 1996	
1997	Full competition in telecommunications. Sale of spectrum. Part sale of Telstra.	Communication services

[a] The dotted line marks the beginning of the high reform period.

Sources: de Laine, Lee and Woodbridge (1997), IC (1998), PC (1999).

In other words, the technology explosion may have altered the way in which technological change and the relative demand for skilled labour are linked (see box 3.2). If, as suggested by Autor et al. (1998), computers and computer-based technologies have qualitatively altered the capital–skill nexus, this should be more easily discerned with respect to machinery and equipment (including computers) and software assets, than with respect to buildings and structures. For this reason, the total capital stock variable is disaggregated into its various components prior to estimation.

3.3 Dataset

The analysis in the subsequent chapters is based on a dataset constructed for this project using ABS data. The details for the individual series are outlined, and brief descriptive statistics provided, in appendix A. This section gives a brief outline of some of the implications for results of the proxies used to measure skill and technological change.

Measurement of skill

An accurate measure of skill is required to explore the impact of technological change on the skill composition of employment and the wage bill. The extent of this relationship depends largely on how skill is defined. For example, broadly defined, skill measures do not capture many changes between skill categories, and may therefore understate the extent of change in the skill composition of employment (and the wage bill) relative to more specific measures. Moreover, skill upgrading can occur within any category, no matter how narrowly defined.

Since skill is a multidimensional concept there is no direct or commonly accepted measure indicating the skill level of the employed workforce.[5] For this reason, in empirical work, proxies based on educational attainment or occupational classifications are often used. While these two measures are highly correlated, an ideal measure of skill would cross–reference occupational classification,

[5] Most jobs require a variety of skills for satisfactory task completion — ranging from physical attributes such as hand–eye coordination, analytical and problem solving capabilities and interpersonal skills. In turn, each attribute requires different levels of formal and on–the–job training (Colecchia and Papaconstantinou 1996).

educational attainment and job requirements.[6] However, these data are not routinely collected.

Occupation is used in this paper to denote the skill level of the workforce. The construction of a consistent time series of employment by occupation was hampered by several changes in ABS occupational classifications since the mid–1970s. Where necessary, data have been reclassified to the first edition of the Australian Standard Classification of Occupations (ASCO1) (see appendix A).

Box 3.2 **Computers and the demand for skilled workers**

According to Autor et al. (1998), computer technology may influence relative labour demand in several ways:

1. routinization of many simple and repetitive white-collar (clerical) tasks;
2. automation of many production processes; and
3. increase in the returns to creative use of greater available information to more closely tailor products and services to customers' specific needs and to develop new products.

They note that both the substitution effects (1 and 2) and the complementarity effect (3) predict that computerisation will be accompanied by an increase in the relative demand for highly educated workers.

Johnson (1997) provides a related analysis of the role of computers. He states that they can make skilled workers more productive in the jobs they already perform (eg architects and CAD), or they can make skilled workers more efficient in jobs formerly done by unskilled workers (eg robots in manufacturing). However, Haskel and Heden (1999) caution that computerisation appears to have reduced the demand for *manual* workers, whether they are skilled or not.

Finally, the purported effect of computers on the demand for skilled labour must be viewed in context. Autor et al (1998) found that computers are often introduced at the same time as organisational changes, new management methods, training and decentralisation. Thus, it is possible that the wage premium associated with computer use (Krueger 1993) is, in reality, attached to the sum total of changes introduced, rather than to computers *per se*.

ASCO1 divides the workforce into eight major occupational groupings. This paper defines skilled employment as an aggregate of the first three of these groupings — managers and administrators, professionals and para-professionals. This grouping is

[6] For example, most high skilled occupations require post school qualifications while many lower skilled occupations do not require any formal training beyond secondary school (Barnes et al. 1999).

commonly referred to in the literature as ‘white collar high skilled’ (high skilled) employment (for example, see Colecchia and Papaconstantinou 1996 and Barnes et al. 1999).[7] Generally speaking, an increase in the share of high skilled workers indicates a more skilled workforce.

Nonetheless, it needs to be recognised that this measure of skill has some limitations. For instance, the allocation of broad ASCO1 occupations to high and low skilled is not entirely exact — as some occupations may include heterogeneous skills.[8] For example, some clerical work requires formal training and skills similar to professionals — such as in areas of accounting and using new computing technologies (Barnes et al. 1999). Also, the skill content of high skilled occupations may change over time.

Measurement of technological change

At the aggregate level, there are several different types of proxies available which attempt to track the pace of technological change (see box 3.3). A commonly used and directly observable indicator is research and development (R&D) expenditure as a share of GDP — or R&D intensity as it is commonly referred to. Research and development is an important input into the generation of new technologies (PC 1999). An increase in R&D intensity suggests an increase in the growth of the stock of technology as more resources are devoted to the innovation process. At the sectoral level, R&D intensity is defined as the ratio of R&D expenditure to value added.

As a measure of technological change, R&D intensity has some limitations, which include the following:

- R&D expenditure does not necessarily say anything about the extent of technological change in the economy. This is because R&D is essentially a search process and the returns are not easily predicted (PC 1999);
- the level of R&D expenditure undertaken by a country ignores any international spillovers arising from the public good nature of knowledge; and
- the concept of spillovers applies intersectorally as well. R&D undertaken in one sector may influence the process of a separate, unrelated sector. An example is

[7] The remaining occupations are grouped as follows: blue collar high skilled (tradespersons); white collar low skilled (clerks and salespersons and personal service workers); and blue collar low skilled (plant and machine operators and drivers, and labourers and related workers). For convenience we refer to these three remaining categories, collectively as ‘lower skill’ workers.

[8] This is particularly true for high levels of aggregation. A more precise allocation of individual occupations to skill groups would require very detailed data, which are not available to this study.

the use of just-in-time inventory management systems (developed in the manufacturing sector) in the restaurant industry.

Other measures and their relative strengths and weaknesses are outlined in box 3.3. The R&D intensity measure is chosen because it has the advantage of being reported in measurable terms. It is also available at the level of disaggregation required by this study. Finally, it is the technological change proxy variable most commonly found in the literature. This has the benefit of allowing comparisons to be made across studies.

Other data issues

The variables were collected for 15 ANZSIC industry divisions and 8 ANZSIC manufacturing subdivisions — compared with, for example, the 450 manufacturing industries used by Berman et al. (1994). This high level of aggregation must be kept in mind when interpreting the results of the analysis, as it has a number of consequences. The broad classification of industries will understate movements in employment between industries. Further, it will not allow nuances of more specific industry development to be captured. For instance, the telecommunications industry has seen some of the most rapid technological advancement of any industry, yet its observed demand for skilled labour will be tempered by other communications sector subdivisions such as postal services.

The level of aggregation also affects the skill measures. Any skill upgrading within a skill classification will not be captured. Thus, acquiring advanced training needed to operate increasingly sophisticated IT equipment, but still being classified as a 'manager', will not be reflected in these results.

Box 3.3 **Measuring technical change**

The problem of measuring technical change is well known. It is a nebulous concept and far more difficult to measure than say, labour, the measurement of which is also subject to debate. Technological change can be measured by residual estimation (for example, total factor productivity) or direct measurement through proxy variables or indicators. For time series analysis, a major problem is that the measure is likely to pick up such variables as changing demand conditions, supply shocks, unmeasured prices movements and so on rather than just technical change on its own. This is a common criticism of the use of total factor productivity as a measure of technological change.

Chennells and Van Reenen (2000) identify three types of measures of technology used in the literature; inputs into the knowledge production function, outputs from the knowledge production function and subsequent diffusion of these outputs around the economy.

Inputs

The most common measure of inputs is R&D expenditure. This measure has the advantage of being measured across time and in a reasonably standard way. It is also reported in terms of a unit of currency which provides a natural weighting and is easier to use than other more qualitative measures of innovation. However, R&D is subject to spillovers and lagged effects. The transmission of knowledge spillovers from R&D is poorly understood. Large expenditures on R&D might not produce output for years, if at all.

Traditionally Australia has lagged behind other OECD nations in its R&D spending as a proportion of GDP (IC 1995). That trend has changed since the early 1980s. Since 1984, R&D expenditures in Australia have increased at a rate of over 10 per cent per annum in real terms. This growth largely reflects a shift towards development research and away from basic research (PC 1999).

Outputs

Patents are the standard way to measure technology outputs. The problem with patents is that a large number of them appear to be of very low value, or obtained as a precautionary measure and never implemented. They also suffer from the same spillover and lagged effects as R&D, with the additional problem of having to deal with count data.

Growth in patent applications in Australia has accelerated over the past 20 years. This was largely driven by the growth in the number of applications lodged by foreign residents (PC 1999). Using Australian-issued only patents as a measure of technology would understate the innovative impact of these patents in the presence of spillovers.

(Continued next page)

Box 3.3 **(continued)**

Diffusion

Diffusion of output is probably the closest measure of what is actually thought of as technological change. A common example of this would be the use of computers by firms. However, researchers are faced with the problem of deciding what this measure actually includes — what sort of computers are employed (word processors, mainframes); what they are employed for (CAD, robots, faxing); and how to weigh these different usages. Also, measuring diffusion over time is difficult if the same technology applied in 1978 is not considered ‘innovative’ in 1998.

Australia has started to collect measures of technological diffusion. The Australian Workplace Industrial Relations Survey (AWIRS) asks respondents questions about process or product innovation, and on the implementation of new technologies and/or computers. The Business Longitudinal Survey (BLS), a firm-based survey instituted by the Australian Bureau of Statistics in 1994, also asked questions dealing with firm innovation. However, the AWIRS data cover two years (1989-90 and 1995) and the BLS just three (1994-95 to 1997-98).

Sources: Chennells and Van Reenen 2000; IC 1995; PC 1999. Australian Bureau of Statistics.

The analysis presented in the next few chapters is aggregation-specific, therefore. As such, it does not lay claim to capturing all the intricacies and detail of a real economy. Nonetheless, the dataset is an improvement over earlier studies. It has broader coverage, going beyond manufacturing to include services and primary industries. The use of occupation categories allows the skill proxy to be defined in terms of high skilled workers, rather than the usual non-production workers. The dataset encompasses time series covering the period 1978 through 1998. This allows trends to be captured over time, as well as cross sectionally. Finally, the paper is able to elaborate on existing studies by examining disaggregated measures of capital stock, including the value of software, for the division level data. It can be argued that capital embodies technical change and that increased capital expenditures may be a reflection of businesses’ need to keep technologically up-to-date. Expenditures on capital equipment may also be a means for parts of the economy to access advances made in other sectors. Therefore, the high skilled workers–technological change relationship is explored more comprehensively through the capital variable.

4 Decomposition of the change in the employment share of high skilled workers

As mentioned in chapter 3, the validity of the two main hypotheses put forward to explain the shift in demand towards high skilled workers — trade and SBTC — may be assessed on the basis of whether economywide changes in the proportion of these workers are due to — respectively — changes between industries or within industries.[1] In the next section, decomposition analysis is used to apportion the economywide change in the share of high skilled workers in employment to between and within effects. In the following section, this exercise is repeated at the broad sectoral level. The sectoral approach is regarded as a test of the pervasiveness of SBTC, as it abstracts from the weight of any particular industry in the economywide results (see box 4.1). In a further test of the pervasiveness of SBTC, both the economywide and sectoral within effects are disaggregated into gender-specific effects. The final section summarises the results of the decomposition analysis.

4.1 Economywide decomposition

Table 4.1 reports the between/within/by gender decomposition of the average annual percentage point change in the share of high skilled employment across all industries (further results can be found in appendix B). The results are reported for the two subperiods 1978 to 1985 and 1986 to 1998. These subperiods are chosen to:

- represent periods of differing intensity in microeconomic reforms in the Australian economy (see chapter 3); and

[1] This dichotomy is a simplification. Trade may have within effects by causing industries to adopt new technologies. Conversely, Haskel and Slaughter (1998) note that it is possible for technological change to have between-industry implications. For instance, technological change may create between effects due to the increasing importance of high technology industries — such as the move towards e-commerce activities. However this effect has been shown to be minor (if at all).

- coincide with the change in occupational classifications in 1986 from the Classification and Classified List of Occupations (CCLO) to the first edition of the Australian Standard Classification of Occupations (ASCO1) (see appendix A).

Box 4.1 **The sectoral approach to decomposition analysis**

In the decomposition analysis framework used here (see appendix B), an industry's contribution to the overall (economywide) within effect is influenced by that industry's share of total employment. Thus, the greater that industry's share (on average over the period), the greater its influence on the total within effect. For this reason, it is possible for, say, a negative change in the proportion of high skill workers in one industry to swamp the positive within contributions made by other industries. From this, it may be erroneously concluded that within industry skill upgrading is not a pervasive phenomenon in the economy.

A partial solution to this problem consists of lowering the coverage of the decomposition analysis from economywide to sectorwide. While large industries will continue to have a disproportionate influence on the overall within effect of the sector to which they belong, decompositions conducted on the other sectors will be immune to it. Thus, the sectoral approach may be regarded as a more stringent test of the pervasiveness of within effects, and hence of SBTC.

A shortcoming of the sectoral approach is that the interpretation of trade effects is not quite as clearcut at the sectoral level as it is at the economywide level. This is because between effects in a sectoral decomposition analysis reflect the reallocation of employment between industries within a single sector. The traditional trade hypothesis interpretation of between effects is based on movements of labour from import-competing industries to other industries, at the level of the economy or within the manufacturing sector. This interpretation may not be as readily applied to between movements in the services sector, for instance, where most service industries produce non-traded goods. Nonetheless, it may be argued that some between movements in the services sector are trade related — for instance, increased employment in the transport and storage industry could be linked to greater trade openness. Also, some services — such as insurance and financial services — are increasingly traded.

In the final analysis, however, the sectoral decomposition approach is more valuable in that it allows a clearer picture of the pervasiveness of within effects within the economy, regardless of what may have caused between changes.

A comparison of the two subperiods shows that, although the share of high skilled workers in total employment increased at roughly similar rates, the dominant effect differed. In the earlier period, the between effect accounted for 60 per cent of the total change. In the latter period, within industry changes dominated, contributing around 80 per cent of the annual increase in the share of high skilled workers.

Beyond the traditional between–within dichotomy, the SBTC hypothesis may be investigated further through the gender breakdown of within-industry skill upgrading. If both males and females employed in an industry are becoming more skilled, this may be regarded as further evidence of pervasive SBTC. If, on the other hand, one gender is upskilling while the other is not, this could be regarded as a sign that this industry is undergoing structural changes such that more jobs are being created which are predominantly staffed by skilled workers of one gender (for example, nurses and teachers in the health and education industry). Another possibility is that an industry is upskilling in response to government incentives to recruit high skilled workers of a particular gender (contained, for example, in equal opportunity and/or affirmative action policies); again, this type of effect would be brought to the fore by the gender breakdown.

For these reasons, it is useful to ascertain whether the within-industry effect is due to skill upgrading by both genders. To this end, this effect is broken down into a net share effect and gender upskilling effects. The former measures the effects of a change in an industry's gender balance, keeping the proportion of males and females with high skilled jobs constant.[2] The latter measures the effects of skill upgrading within each gender.[3]

The gender decomposition presented in table 4.1 shows that within-industry upskilling is due to skill upgrading by both genders, albeit at different rates. While the male rate remained constant across periods, the female rate accelerated considerably in the latter period.[4] The negative net share effect is a reflection of the increasing female labour force participation in both subperiods.

[2] Given the male and female propensities to be employed in high skilled occupations (see figure 2.1), a positive net share effect reflects an increase in the proportion of males employed by an industry, and vice versa for females.

[3] A detailed exposition of the overall and gender specific decomposition techniques is presented in appendix B.

[4] According to Green et al.'s (2000) analysis of a similar trend for the UK, this is partly due to the faster expansion of computer usage in women's jobs.

Table 4.1 **Decomposition of changes in the economywide share of high skilled employment, 1978 to 1998**

Annualised percentage point change

		1978–85	*1986–98*
Total		0.30	0.29
Between		0.18	0.06
Within		0.12	0.23
of which:	• Net share	-0.02	-0.02
	• Male upskilling	0.10	0.11
	• Female upskilling	0.04	0.14

Source: Commission estimates from unpublished ABS *Labour Force Survey* data.

4.2 Sectoral decomposition

Table 4.2 shows the results from decomposing changes in the share of high skilled workers for each of the four sectors separately — rather than across all sectors, as was the case in table 4.1. It also shows the contributions of the three gender effects to the overall within effect for each sector. In what follows, results of the within/between decomposition are discussed first, followed by those of the gender decomposition.

The primary sector experienced the only fall in the share of high skilled employment between 1978 and 1998. This fall accelerated considerably between the two subperiods, from 0.04 percentage points annually between 1978 and 1985, to 0.42 percentage points between 1986 and 1998. While the between effect was entirely responsible for overall deskilling in 1978–85, within effects drove deskilling in the latter period. The fall in the share of high skilled workers in the agriculture, forestry and fishing industry between 1986–98 made the largest contribution to this change (see appendix table B.3). In contrast, the increased share of high skilled workers in the mining industry made a positive contribution to the total sectoral effect in both subperiods.[5]

The manufacturing sector experienced the highest growth in the share of high skilled workers of any sectors — 0.41 percentage points per annum between 1986 and 1998. In that period, both between and within effects contributed to skill upgrading in that sector. This was also true of the earlier period, although the total

[5] Between 1986–98, the share of high skilled workers in agriculture, forestry and fishing fell by 4 per cent, while it increased by 8 per cent in mining (data not shown). However, the magnitude of the fall in agriculture, forestry and fishing outweighed the gain in mining — as the former industry accounts for around 80 per cent of total employment in the primary sector.

upskilling effect was only a third of that in the latter period. In both periods, the within effect greatly dominated the between effect.

Table 4.2 **Decomposition of changes in the share of high skilled employment within sectors and by gender, 1978–98[a]**

Annualised percentage point changes

		1978-85	*1986-98*
Primary			
Total		-0.04	-0.42
Between		-0.14	0.04
Within		0.10	-0.46
of which:	• Net share	0.04	-0.02
	• Male upskilling	0.04	-0.15
	• Female upskilling	0.02	-0.29
Manufacturing			
Total		0.14	0.41
Between		0.03	0.01
Within		0.11	0.40
of which:	• Net share	-0.01	0.01
	• Male upskilling	0.07	0.20
	• Female upskilling	0.05	0.19
Utilities and Construction			
Total		0.32	0.25
Between		0.06	-0.15
Within		0.26	0.40
of which:	• Net share	-0.02	-0.02
	• Male upskilling	0.26	0.30
	• Female upskilling	0.02	0.12
Services			
Total		0.23	0.29
Between		0.13	0.06
Within		0.10	0.23
of which:	• Net share	-0.02	-0.03
	• Male upskilling	0.08	0.09
	• Female upskilling	0.04	0.17

a It is important to note that the number of industries in each sector differs. This will influence the between effect for some sectors relative to others. This is because sectors with more industries will capture greater employment shifts than those with fewer industries. The primary sector comprises 2 ANZSIC industry divisions; Manufacturing has 8 industry subdivisions; Utilities and construction has 2 industry divisions and Services has 10 industry divisions.

Source: Commission estimates from unpublished ABS Labour Force Survey data.

Decomposition results for the manufacturing sector in Australia are consistent with those of Borland and Foo (1996). They also accord with findings for other OECD countries. For example, Berman et al. (1994), in their decompositions, found that most skill upgrading in US manufacturing between 1959 and 1987 was due to within-industry effects.

The utilities and construction sector, comprising the electricity, gas and water and construction industries, also increased its share of high skilled workers between 1978 and 1998. In both periods, the bulk of the growth was due to the within-industry component. Indeed, the utilities and construction sector experienced the fastest rate (with manufacturing) of within-industry upskilling of the whole economy for any period, equal to 0.40 per annum on average during 1986–98. The negative between effect in the latter period reflects the fall in employment in electricity, gas and water (see appendix B) — an industry with a higher proportion of high skilled workers than construction (data not shown).

The share of high skilled workers in the services sector rose at an approximately constant and strong rate in the two periods. As with other sectors, the within-industry component dominated skill upgrading during 1986–98. In the earlier period, the greater strength of the between-industry effect was due to the rapid growth of the finance, property and business services and education, health and community services industries (see appendix B).

Results of the gender decomposition by economic sector are also reported in table 4.2 for the two periods. As was done economywide (see table 4.1), the sectoral within effect is broken down into the sum of two gender upskilling effects and a net gender effect. Each sector is now examined in turn.

In the primary sector, the strong rate of within-industry deskilling observed during 1986–98 was due to deskilling by both genders, which was compounded by a negative net share effect. In all likelihood, the concurrence of these effects is a reflection of the decline in the proportion of farmers during that period and in the proportion of males employed in the agriculture, fishing and forestry industry.[6] A reverse pattern was in evidence during 1978–85, with the combination of upskilling by both genders and a net positive share effect resulting in an overall positive within effect.

In contrast to the primary sector, the net share effect played a negligible role in the positive within-industry skill upgrading recorded by the manufacturing sector in both periods. Instead, overall upskilling was driven by both genders being increasingly likely to be employed in high skilled occupations. The rate of upskilling for males and females accelerated significantly during the second period.

[6] Farmers are classified as ‘managers and administrators’ in the ASCO1 classification used here.

While the utilities and construction sector experienced upskilling by both genders in each sub-period, the rate for males was noticeably higher than for females. However, the female rate accelerated considerably more than the male rate in the second period. Moreover, female representation in that sector increased, as reflected in a consistently negative net share effect.

A similar pattern was in evidence in the services sector. Negative share effects between 1978 and 1998 — reflecting the rapid increase in female representation in service industries — dampened the impact of upskilling by both males and females. While male upskilling was more rapid than for females initially, the rate of female upskilling more than quadrupled between 1978–85 and 1986–98, overtaking that for males in the latter period.

4.3 Summary

The decomposition analysis presented in this chapter offers preliminary support for the SBTC hypothesis, for a number of reasons. First, the results show that, for most of the 1978–98 period, the within-industry effect was the main factor driving the increase in the employment of high skilled workers economywide. While the between effect dominated the 1978–85 period slightly, it dropped away during 1986–98, when the within effect doubled in size.

Second, the dominance of the within effect is confirmed at the sectoral level. That is, during 1986–98, all sectors except primary–recorded skill upgrading which was overwhelmingly due to within industry upgrading. This may be regarded as a reflection of the pervasiveness of SBTC in the latter period. While not dominant economywide in the earlier period, the within effect is found to be the main source of sectoral change for all sectors except primary and services.

Third, an examination of gender in within-industry skill upgrading provides a final indicator of the impact of SBTC. This is because gender decomposition results suggest that positive within effects resulted from upskilling by both genders rather than from gender–specific upskilling or compositional changes.

In conclusion, decomposition analysis offers preliminary evidence of the real and pervasive nature of SBTC in Australia. Interestingly, the fact that SBTC appears to have been stronger in the 1986–98 period is suggestive of an association between microeconomic reform and the skill intensity of production. This issue is explored further in the next chapter.

5 High skilled labour and technical change

In this chapter, the preliminary findings obtained in chapter 4 are investigated further using multivariate regression analysis, specifically panel data and seemingly unrelated regression techniques. These modelling procedures allow a more stringent test of the hypothesised association between skill upgrading and technological change affecting the production process. A system of linear equations is estimated where the dependent (explained) variable corresponds to the employment or wage bill share, and the independent (explanatory) variables are the two proxies measuring the use of technology (R&D intensity and capital intensity).[1]

As discussed in chapter 3, the capital stock variable used in the calculation of the capital intensity measure is disaggregated into its components: buildings and structures (B&S) and machinery and equipment (M&E) for manufacturing; and B&S, M&E and software for divisions. This disaggregation represents a more rigorous test of the capital–skill complementarity hypothesis than is found in previous studies. This is because — assuming embodied technology — such complementarity is more likely to occur with machinery and equipment and software than with buildings and structures. Disaggregating the capital variable increases the ability to discern the relationship between embodied technology and skill intensity by removing the effect of buildings and structures on the capital stock variable.

Two sets of equations are estimated — one for manufacturing subdivisions, and one economywide, using division level data. Estimating each dataset as a system has the benefit of allowing the variables in one sector to influence the variables in others. That way, the effect of R&D spending in the mining division influences the estimation of the coefficients in the retail sector, for example (see appendix C).

The coefficients on the independent variables are examined for their significance, sign and value. From these indicators, it is possible to infer the strength, direction and magnitude of the association between technological change on the share of high skilled workers in employment and the wage bill. This association is summarised through an elasticity measure, which is the percentage change in the share of high

1 See appendix C for details of these equations and their derivation.

skilled employment (or wages) in response to a 1 per cent change in the technology variable. A positive (and significant) elasticity is interpreted as providing support for the skill biased technical change (SBTC) hypothesis. Overall, these equations are shown to provide a good fit for the data (see appendix D for details of the econometric results).

In the following sections, selected results from the various regression analyses are summarised and discussed (more detailed and comprehensive results are given in appendix D). Section 5.1 presents the results of the various specifications of the constant returns to scale (CRS) model using manufacturing subdivision data.[2] Section 5.2 does the same with economywide data. Some concluding comments are offered in section 5.3.

5.1 Manufacturing

The main model is estimated in order to capture the relationship between technological change and skill intensity in the manufacturing sector. This model is subsequently augmented by trade variables. Both technology and trade variables are incorporated and the model re-estimated for the low and high reform periods separately.

Main model

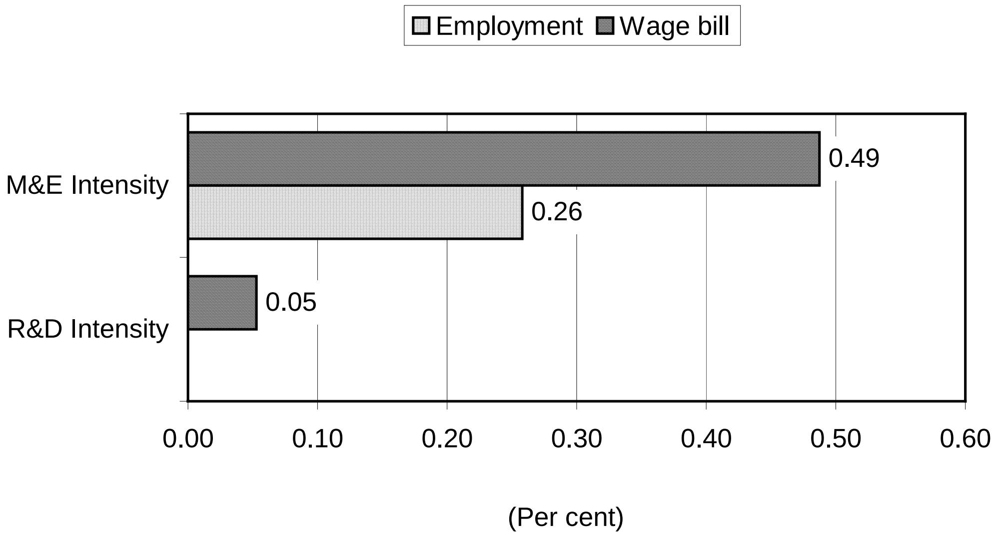
The relatively homogenous characteristics of the manufacturing subdivision data (see appendix A) allow the use of panel data techniques. All subdivision data are used to estimate the aggregate manufacturing sector outcomes (see appendix C). Estimates of the elasticity of employment and wage bill shares of skilled workers with respect to the technology intensity variables are obtained. Selected significant results are presented in figure 5.1 (underlying detailed results are available in appendix table D.2).

A number of observations are warranted in relation to this figure. First, both R&D intensity and capital intensity (as measured by the M&E variable) are significantly and positively associated with the share of high skilled workers in the wage bill. Second, this association is considerably larger for capital intensity. Third, the incidence of the association is consistently greater for the wage bill than for employment.

[2] As outlined in appendix C, there are two versions of the model; constant returns to scale and non-constant returns to scale. Results for the non-constant returns to scale version of the model can be found in appendix D.

Figure 5.1 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to disaggregated technological change variables[c] — manufacturing**

CRS model



a Point elasticity measured at the means. **b** Employment elasticity estimates based on 1978–98 data; wage bill elasticity estimates based on 1986–98 data. **c** Only the elasticities of significant variables are reported.

Source: Constructed from detailed results in appendix table D.2.

The first result noted above lends support to the existence of SBTC in the manufacturing sector; a one per cent increase in R&D and M&E intensity is associated with the share of high skilled workers–being between one twentieth and one half of a per cent higher than it would be otherwise. Thus, the skill requirements of the production process appear to be related to the M&E intensity and the R&D 'effort' of an industry.

One must be careful when interpreting the relative size of the associations. While the capital intensity effect dominates, it should be remembered that the M&E/value added ratio is much larger, on average, than the R&D/value added ratio.[3] This means that a 1 per cent increase in the former involves a far greater increase in expenditure than the latter. The observed difference between the elasticities is not surprising, therefore. On the contrary, it is revealing to find that, in spite of its generally small size, the R&D intensity ratio is significantly associated with higher shares of high skilled workers.

3 The word 'effect' is not used to denote causality, but as shorthand for a significant association between two variables.

The relatively smaller size of the employment share-M&E intensity effect, compared to the wage bill share effect, is of interest. This result could be due to a number of reasons. First, it may reflect the fact that higher levels of M&E intensity are associated with higher employment shares *as well as* higher relative wages for high skilled workers. This may be a result of a supply bottleneck in the market for high skilled workers. However, as observed in chapter 2, the relative wage differential between the two skill groups increased only slightly between 1986 and 1998. Second, the wage bill share result may be capturing movements within the high skilled worker category (for example, from para-professional to manager) which the employment share cannot account for. If it is assumed that a manager earns more than a para-professional, it would be natural for the wage bill effect to dominate the employment effect. A third interpretation could be that the employment-wage bill differential is due to the over-representation of part-time and casual workers in the lower skilled group. As these workers normally carry a greater weight in employment than in the wage bill, the employment effect would thus be constrained below the wage bill effect. Finally, the difference between employment and wage bill elasticities could be due to the fact that they are not estimated over the same period: 1978–98 for employment and 1986–98 for the wage bill. If the relationship between technology use and skilled employment changed over the course of the longer period, then differences with the wage bill results should be expected. This explanation is explored later in the chapter.

Overall, the results summarised in figure 5.1 may be regarded as evidence that the relationship between technological change and skill intensity is twofold: one channel is through the R&D effort of the firm or industry; the second through the installation of machinery and equipment which embodies technological advances, possibly made by other firms or industries. This is of interest because not all firms or industries undertake R&D. For instance, more than half of the manufacturing sector's total R&D in 1997-98 was carried out by the transport equipment industry alone. Even in that sector, only 21 per cent of firms surveyed between 1996 and 1998 undertook R&D, on average.[4] Nonetheless, despite the concentration of R&D activity, its effects are likely to be pervasive, reaching most firms and industries through the purchase of machinery and equipment.

Trade–augmented model

The robustness of the previous section's results to the incorporation of trade variables into the analysis is now tested. Following Machin et al. (1996), the ratio of imports to value added ('import penetration') and of exports to value added ('export

4 Calculated from unpublished *Business Growth and Performance Survey* data (ABS cat. no. 8141.0).

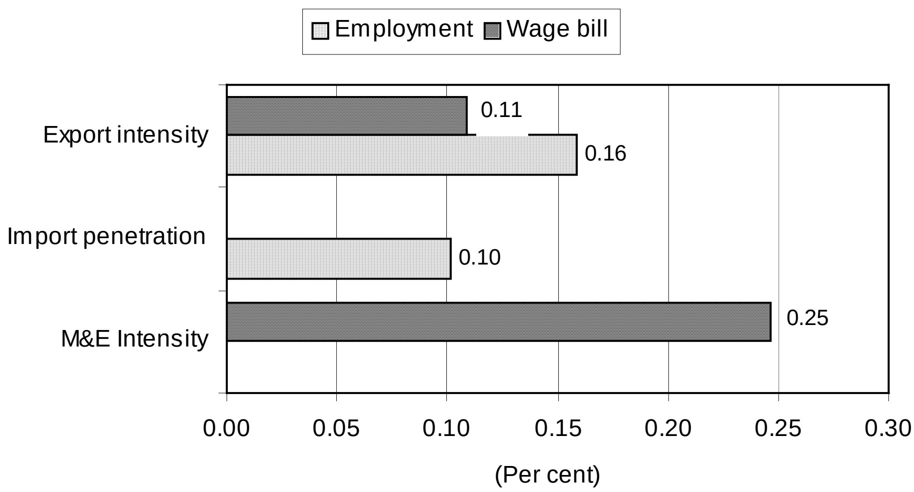
intensity') in each industry is added to the list of explanatory variables for the share of high skilled workers in employment or the wage bill. This forms a trade-augmented model.

This extended model specification is designed to allow the potential roles of technology and trade to be captured simultaneously. This may be regarded as a more powerful test of the explanatory power of the competing SBTC and trade hypotheses in Australia. Overseas studies have shown that the inclusion of trade variables in the regression does not detract from the significance of the R&D intensity effects (Machin et al. 1996, Haskel 1996, Machin and Van Reenen 1998).

The elasticity results derived from the estimation of the extended model are presented in figure 5.2. Again, only results that are statistically significant are included.

Figure 5.2 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to trade and technological change variables[c] — manufacturing**

CRS model



a Point elasticity measured at the means. **b** Employment elasticities estimated based on 1978–98 data; wage bill elasticities estimated based on 1986–98 data. **c** Only the elasticities of significant variables are reported.

Source: Constructed from detailed results in appendix table D.3.

The results shown in figure 5.2 offer limited support for the trade hypothesis. One interpretation of this hypothesis is that competitive pressures from low–wage countries may result in an industry shedding some of its unskilled labour in preference to its high skilled labour. Thus, a positive relationship between the share of high skilled workers in an industry and the degree of import penetration is predicted, and found in the employment share equation.

By contrast, the interpretation of the export intensity elasticities is not readily apparent. While some authors (eg Autor et al. 1998) have regarded positive export intensity effects as support for the trade hypothesis, Machin and Van Reenen caution that ‘it is not always obvious how one should read coefficients on changes in export intensity as the link between rising exports propensities and the extent of [international] competition is not clear’ (1998, p. 1235).

As outlined in section 2.1, the Stolper-Samuelson theorem states that as a country increases its imports, factors used intensively by domestic import-competing industries will be released. Subsequently, the intensity with which other (including exporting) sectors in the economy use these factors will increase (as their relative price has fallen). If one assumes that import-competing sectors in Australia are intensive in their use of lower skilled labour, then greater foreign competition should see the share of lower skilled labour increase. Thus, a negative, rather than positive, coefficient on export intensity would be expected if the trade hypothesis was supported.

The positive and significant export intensity elasticities illustrated in figure 5.2 are not necessarily consistent with the trade hypothesis and inconsistent with SBTC, therefore. Indeed, it is plausible that businesses competing in the global economy are forced to adopt the most technically–advanced means of production (irrespective of the relative wages of high and lower skilled workers). The fastest growing segment of manufacturing exports is ‘other manufacturing’. As shown in appendix A, this category includes industries such as photographic and scientific equipment, electronic equipment and industrial machinery and equipment. The manufacturing processes for these goods utilise relatively advanced manufacturing techniques compared with more traditional industries such as food, beverages and tobacco. Thus, positive export intensity elasticities may simply be a reflection of the relationship between export led technology adoption and skill intensity.

This interpretation is reinforced by the fact that the elasticity of the wage bill share with respect to the machinery and equipment intensity variable remains significant in the results reported in figure 5.2. This indicates that embodied technology is significantly associated with skill intensity, notwithstanding trade-related effects which may be taking place simultaneously. Furthermore, this variable has an elasticity value which is larger than that of the trade variables. On the other hand, R&D intensity is no longer significant when trade variables are incorporated into the estimating equation, which further favours the embodied — rather than firm-developed — technology reading of these results.

On balance, results from the model provide only limited support for the trade explanation for the changing demand for high skilled workers. While the import penetration elasticity supports this explanation, its magnitude is overshadowed by the elasticities with respect to machinery and equipment and export intensity, both of which are thought to reflect technology rather than trade effects.

High and low reform periods

The strength of the trade and technology effects in the employment share regression is now tested for both the low and high microeconomic reform periods (1978–85 and 1986–98 respectively).[5] The rationale behind this sub-sampling exercise is related to both the trade and the SBTC hypotheses. With respect to trade, there is evidence that, from the mid-1980s onward, government policies designed to improve the operating environment and incentive structure faced by Australian firms also provided significant impetus to stronger export performance in manufacturing (Clark et al. 1996). Thus, it is of interest to examine whether the relationship between export intensity and skill intensity altered during the high microeconomic reform period.

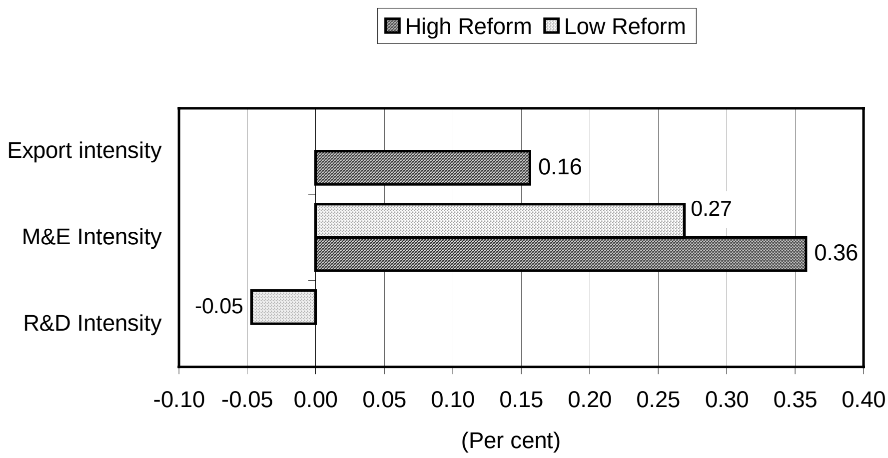
The surge in manufacturing exports also underlies the need to examine the specific role technology may have played during the high reform period. From 1990 onward, elaborately transformed manufactures (ETMs) provided the bulk of the growth in exports (Clark et al. 1996). Given that a significant proportion of ETMs is made up of products which are technology intensive (automobile and aircraft components, chemicals, office and communication equipment), it is likely that this high level of export performance was only achieved through the use of sophisticated technology. Again, technology intensity could be reflected in export intensity.

The results of the re-estimation of the model are summarised in figure 5.3. The salient result from this graph lies in the consistent, positive and significant elasticity of the employment share of high skilled workers with respect to the ratio of machinery and equipment to value added. While this intensity variable is associated with a higher share in both periods, the strength of the association increased by a third during the high reform period. This could be an indication of the fact that microeconomic reform created incentives for producers to reconsider their usage of skills and technology in the production process. An alternative explanation may lie in the fact that the mid-1980s marked the beginning of the explosion in the use of personal computers. This type of equipment has come to symbolise SBTC in the literature, and is generally regarded as having a different impact from other forms of machinery (see, for example, Autor et al. 1998).

[5] Wage data are only available for 1986–98 so this exercise cannot be replicated in terms of the wage bill share.

Figure 5.3 **Elasticity[a] of the employment share of high skilled workers with respect to trade and technological change variables[b] — manufacturing, high and low reform periods**

CRS model



a Point elasticity measured at the means. **b** Only the elasticities of significant variables are reported.

Source: Constructed from detailed results in appendix table D.4.

As expected, the association with export intensity is significant in the high reform period. The fact that it is not significant in the low reform period reinforces the view that it is the underlying technology intensity, rather than exports *per se*, which are behind this result. This interpretation is reinforced by the fact that import penetration is no longer significant. Given that the floating of the Australian dollar in 1983 preceded the beginning of the high microeconomic reform period by three years, a strong trade effect should have been discernible in the low reform period, if present.[6] The fact that during that period, neither export intensity nor import penetration show any significance while machinery and equipment is significant and positive lends further credence to the SBTC hypothesis. This is in spite of a slightly negative R&D intensity elasticity during that period. The direction of that relationship may be an indication that what R&D activity was carried out prior to 1986 was mainly aimed at substituting technology for skilled workers.

6 The floating of the dollar is generally regarded as the beginning of the ‘opening up’ of the Australian economy.

5.2 Economywide

The regression analyses performed on the industry division data follow the same sequence as those for the manufacturing data. The model is progressively extended from technology-only explanatory variables to trade–augmented variables to high and low reform periods.

Main model

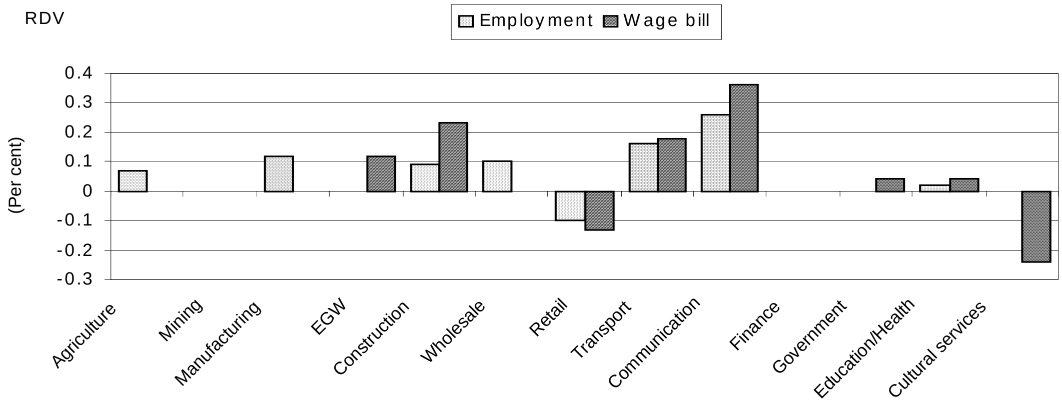
For the division data, econometric testing showed that technology variables do not affect all industries in the same way (see appendix D for details). This is not surprising given the diversity of industries covered in this dataset (from primary industries to services). Therefore, the approach taken to analyse these data allows for inter-industry variation in the coefficient estimates — and hence the elasticities — linking each explanatory variable to the share of high skilled workers in employment and the wage bill. However, coefficients are still jointly estimated so that cross–sector influences are captured. This differs from the manufacturing results presented earlier, where a single coefficient was estimated for the entire subdivision dataset.

The results of the estimation of the model based on division data are summarised in figures 5.4 through 5.7. Detailed results are available in appendix table D.7.

As shown in figure 5.4, a significant and positive association between R&D intensity and the employment and wage bill shares of high skilled workers is detected for a majority of industry divisions. Only in retail and cultural services is the R&D variable associated with lower proportions of skilled workers. In the retail industry, the M&E intensity (M&E/Y) coefficient is positive (figure 5.5), raising the possibility that the operation of installed capital requires high skilled personnel, while the development of new technologies is done as a high skilled labour saving technique.

Figure 5.4 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to R&D intensity — divisions[c]**

CRS model

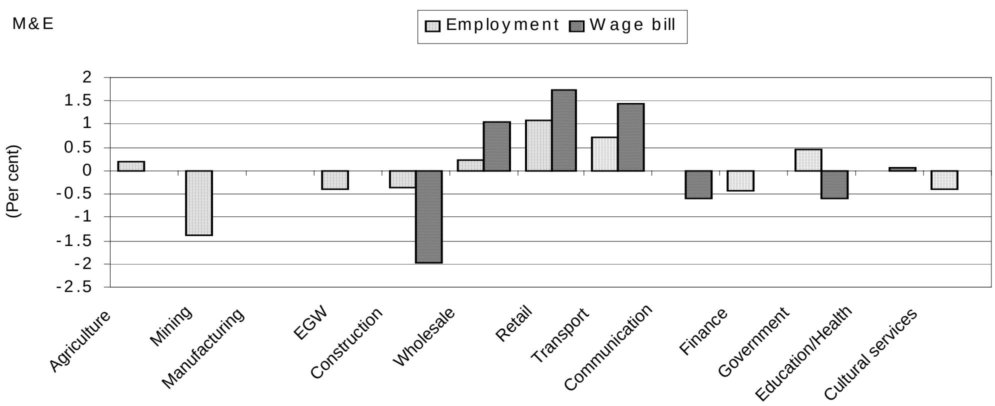


a Point elasticity measured at the means. **b** Employment elasticity estimates based on 1978–98 data; wage bill elasticity estimates based on 1986–98 data. **c** Two divisions, accommodation and personal services, have been left out of the estimation due to missing observations.

Source: Constructed from detailed results in appendix table D.7.

Figure 5.5 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to machinery and equipment intensity — divisions[c]**

CRS model

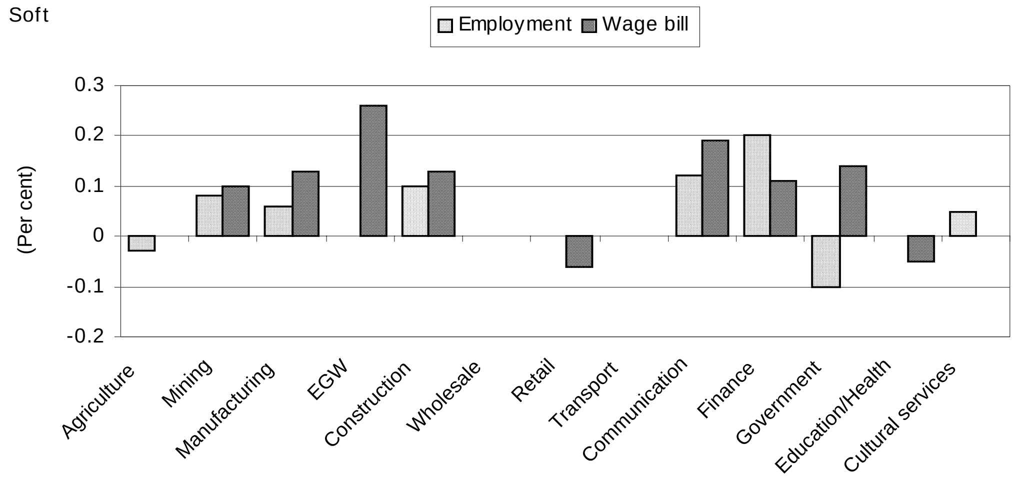


a b c See notes from table 4.7.

Source: Constructed from detailed results in appendix table D.7.

Figure 5.6 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to software intensity — divisions[c]**

CRS model

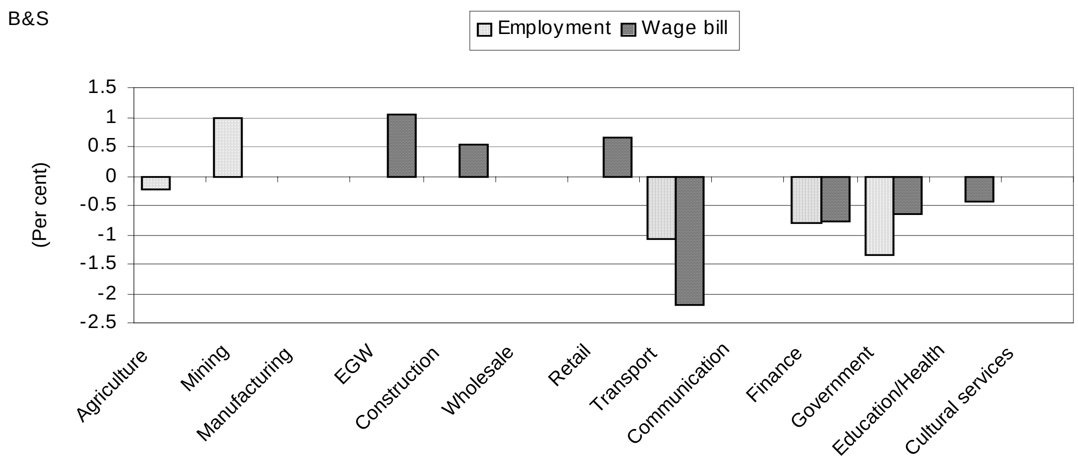


a b c See notes from table 4.7.

Source: Constructed from detailed results in appendix table D.7.

Figure 5.7 **Elasticity[a] of the employment and wage bill shares[b] of high skilled workers with respect to buildings and structures — divisions[c]**

CRS model



a b c See notes from table 4.7.

Source: Constructed from detailed results in appendix table D.7.

Overall, elasticities with respect to M&E intensity are mixed (figure 5.5). While some industries show a positive association between M&E intensity and the share of high skilled workers, in others the reverse is the case. The latter result would seem to indicate that an increase in capital intensity is associated with a fall in the proportion of high skilled workers in the total wage bill. This could be interpreted in at least two ways:

- substitution is occurring between capital and high skilled labour. However, capital intensity does not appear to exert a significant influence on employment shares of high skilled workers; or
- capital–intensive industries pay high skilled workers relatively less compared with other industries. This explanation would suggest that the differential impact of technological change on the marginal productivity of high skilled and lower skilled workers is not as strong in capital intensive industries. This effect need not prevail economywide: a few capital intensive industries, such as mining or stevedoring, paying their lower skilled workers high relative wages, may be sufficient to drive this regression result.

The negative sign of several M&E intensity elasticities does not necessarily invalidate the SBTC hypothesis in these industries, only that part which posits capital–skill complementarity. The majority of positive and significant results in the software variable are more telling.

The importance of software intensity (software/Y) relative to machinery and equipment is particularly apparent in manufacturing, where the former is the only asset for which a significant relationship with skill share was detected (figure 5.7). The comparison with the manufacturing M&E intensity elasticities in section 5.1 (figure 5.1) reveals, therefore, that the M&E–skill complementarity detected at the time was primarily due to the influence of computers on which the software is run. This underlines the need to understand the relationship between different types of investment and the changing demand for labour. This need can be further illustrated in terms of the construction industry, where elasticities of opposite signs are detected for equipment and software (figures 5.5 and 5.7). This suggests that, in that industry, investment in non-computing machinery and equipment is skilled labour saving while investment in computers and software is skilled labour enhancing.

The only three industries for which machinery and equipment is positive and significant both in terms of wages and employment — wholesale, retail and transport — have either insignificant or negative elasticities on software. This apparent inconsistency may be a reflection of the fact that the software they use may have been purchased at the same time as the hardware, in which case its value would appear under machinery and equipment in ABS statistics.[7]

Finally, the significance of buildings and structures intensity (B&S/Y) is less than that of other assets, overall, and the elasticities are mostly negative (figure 5.6). This confirms the suspicion that the level of capital stock aggregation affects the results. Agriculture, transport, finance, government and education all show significant negative elasticities for the buildings and structures variable. Among these divisions, only finance also has a significant negative machinery and equipment elasticity, and only education also has significant negative software elasticity. This suggests that buildings and structures differ fundamentally from other assets in their relationship with the demand for skill intensity in the production process.

These results point to the desirability of disaggregating the capital stock when ascertaining the existence of SBTC. While, as expected, buildings and structures are of little consequence for skill intensity, this is not true of other types of assets. The software variable, in particular, provides added support to the SBTC hypothesis. The more computer intensive an industry, the more likely it is (on average) to employ high skilled workers.[8] The fact that M&E intensity does not appear as a consistent influence may be a reflection of the fact that the scope for technological advances to be embodied in this type of asset differs between industries. To take an example, machinery and equipment used in the transport and storage industry do not undergo very fundamental quality changes, in contrast to equipment in use in the communication industry. In the ‘no scope’ industries, therefore, the primary motive of investment may be to substitute capital for high skilled labour.

Overall, the results for the division data reveal differing influences on the number of high skilled workers hired and the wages they receive. The fact that R&D exerts a much stronger influence on wage bill shares than on employment shares may be indicative of a supply bottleneck in the market for skills. Given such a bottleneck, the number of high skilled workers hired would not change greatly due to SBTC, however the wage premium paid for these workers would increase.

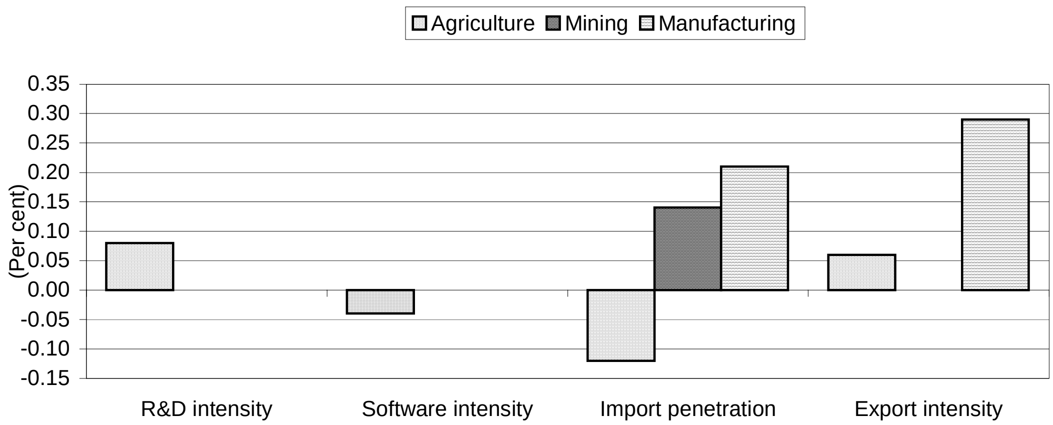
Finally, it is worth noting that the magnitude of the elasticities illustrated in figures 5.5 and 5.6 is a lot higher, in some industries, than the equivalent elasticities in section 5.1. This is to be expected since the industry pooling approach adopted for manufacturing in that section has an averaging effect on the elasticities.

[7] The purchase of ‘bundled’ software is more likely to be a relevant consideration for small businesses.

[8] This does not imply causality between computers and skilled workers. It may be the case that having relatively more skilled workers causes industries to adopt computer intensive production processes. The most likely causality, however, is running from industries’ choice of technology to their choice of high skilled workers.

Nonetheless, it is of interest that, according to figure 5.4, the effect of a 1 per cent rise in R&D intensity on the wage bill share variable can be as high as 0.35 per cent (in communication services), while the M&E intensity elasticity can be as low as -2 per cent (in construction).

Figure 5.8 **Elasticity[a] of the employment share[b] of high skilled workers with respect to trade[c] and technology variables — divisions[d]**
CRS model



a Point elasticity measured at the means. **b** No significant results were recorded for equivalent wage bill share regressions. **c** Merchandise trade data are only available for agriculture, mining and manufacturing. **d** Results are reported only for those industries for which the elasticity with respect to the selected explanatory variable is significant.

Source: Constructed from detailed results in appendix table D.8.

Trade–augmented model

Trade data are only available for three divisions — agriculture, mining, and manufacturing. Thus, caution must be exercised in generalising the results from this model variant.[9] Another reason for caution is the fact that significant results were obtained only in relation to employment share regressions. The results of the estimation of the model containing technology and trade explanatory variables are summarised in figure 5.8 (detailed results are presented in appendix table D.8).

The overall effect of introducing trade variables into the regression is a reduction in the significance of the other variables in the employment share regressions. Only in agriculture do the elasticities on R&D intensity and software intensity retain their

9 Expanding the notion of import penetration beyond industry-specific measures was explored by including an economy-wide measure. This allowed the model to capture any reallocation effects between traded and non-traded sectors. Estimations including the non-traded services sector, however, showed no qualitative change in the basic results.

sign and significance from figures 5.4 and 5.7. In manufacturing and mining, no non-trade variable remains significant.

The signs of the import elasticities are of interest for the three industries examined. In agriculture, the negative elasticity is at odds with expectations based on the trade hypothesis. In mining and manufacturing, positive elasticities are consistent with the trade hypothesis, implying that increasing imports are associated with increasing shares of high skilled workers. However, the more detailed manufacturing analysis of sections 5.1.2 and 5.1.3 provide strong support for SBTC. Finally, in mining, the possibility of trade effects cannot be rejected, given that import penetration has the only significant elasticity. However, it is doubtful whether an industry with an import penetration coefficient averaging only 15 per cent between 1978 and 1998[10] is likely to have experienced a change in its skill worker mix due to overseas competition.

While it could be said that the model using division data provides some support for the trade hypothesis in Australia, this would be unwarranted for a number of reasons. First and foremost, the restricted coverage of this model does not permit generalisations. Second, the fact that no wage bill regression is significant casts doubt on the robustness of the employment share results. Third, industry specific results are far from consistent, with agriculture and manufacturing showing no or only partial signs of trade effects. Fourth, even in the case of mining, there is uncertainty regarding the capacity of imports to exert a significant influence on skill intensity.

High and low reform periods

As mentioned in the previous section, no significant results were detected when trade variables were added to the wage bill regressions for industry divisions. While this could be due to a variety of factors, a reason may lie in the combination of shorter time series and the greater number of explanatory variables. It could be that, if estimated on the same time period basis, employment share regressions would also lose their explanatory power. On the other hand, as was found in relation to manufacturing, it could be that any economywide association between technology and skill intensity comes into sharper focus if high and low reform periods are examined separately (1986–98 and 1978–85 respectively).

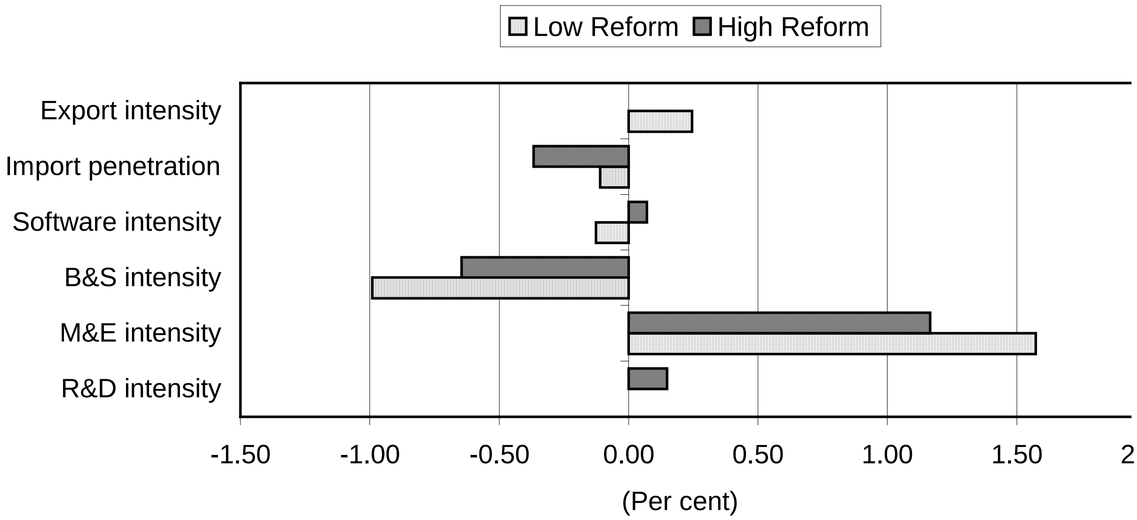
In order to shed light on these possible explanations, the dataset is once again split timewise into the two reform periods, and the trade–augmented model re-estimated for each sub-sample. A lack of sufficient observations precludes individual

[10] Compared with 85 per cent in manufacturing.

industries being distinguished, so that the elasticities presented in figure 5.9 apply jointly to the three industries for which trade data are available: agriculture, mining and manufacturing.

Figure 5.9 **Elasticity[a] of the employment share of high skilled workers with respect to trade and technology variables[b] — divisions[c] — high and low reform periods**

CRS model



a Point elasticity measured at the means. **b** Results are reported only for those variables for which the elasticity is significant. **c** Merchandise trade data are available for agriculture, mining and manufacturing only.

Source: Constructed from detailed results in appendix table D.9.

The high reform period is strongly supportive of SBTC, and casts doubt on the strength of the trade effects detected primarily in mining over the entire period (see figure 5.9). In the low reform period, there is evidence of capital–skill and exports–skill complementarity. In the high reform period, the former effect intensifies while the latter drops away. The most striking result concerns the signs of the software and R&D variables; from negative or non-significant in the low reform period, they become positive and significant in the following period. This reversal confirms the thrust of the findings for manufacturing concerning the association between SBTC and the period of intensive microeconomic reform. The results in figure 5.9 also cast doubt on the validity of the trade effects detected in relation to mining and manufacturing in figure 5.8. On a three-industry, two-period basis, these effects disappear, to be replaced by negative and significant import elasticities. Further, the strength of the import elasticity in the high reform period is more than three times that in the low reform period, suggesting that trade is not having the effect anticipated by the trade hypothesis.

5.3 Conclusion

Overall, there is evidence of SBTC occurring in the Australian economy. Using R&D intensity and capital intensity as proxies for the level of technology, results presented in this chapter show that the more technology intensive an industry, the more likely it is to have high skilled workers making up a large proportion of its total wage bill or, somewhat less robustly, of its total workforce.

The strongest and most consistent evidence of SBTC is detected in the manufacturing sector. In that sector, a 1 per cent increase in the ratio of machinery and equipment to value added is associated with the share of high skilled workers in the total wage bill being up to half a per cent higher. Starting from a much lower base, a 1 per cent increase in the ratio of R&D expenditure to value added is associated with that share being up to 0.05 per cent higher.

Economywide, evidence of SBTC is stronger in some industries than in others, and greater for R&D intensity than machinery and equipment intensity. This is likely to reflect the greater diversity of industries examined, and the fact that some industries have little scope for new technologies ('homegrown' or 'adopted') to affect the skill mix. Nonetheless, a majority of industry divisions show at least some signs of SBTC. In some instances, the association between technological change and the share of high skilled workers is sizeable. In communication services, for example, a 1 per cent increase in R&D intensity is associated with the wage bill share of these workers being 0.35 per cent higher than otherwise, which is significantly larger than the (subdivision average) relationship detected in manufacturing. By contrast, in other industries such as government services and utilities, the adoption of technological change appears to be used primarily as a means of substituting for skilled workers.

For the whole economy, the role of technological change is also underlined by software (and computers), which appear to be the main conduit for SBTC occurring via additions to the capital stock.

When trade variables are incorporated into the analysis, a consistent trend emerges from the manufacturing and division data. This trend reveals a strong association between export intensity and skill intensity. In many cases, this association overshadows more direct measures of technology, previously detected in the non-trade version of the model. With regard to manufacturing (division and subdivisions), the strength and consistency of the export results are not matched by the explanatory power of the import penetration variable, which supports a technology explanation. In mining, the possibility of trade effects cannot be entirely discounted as import penetration has the only significant elasticity for that industry in the trade–augmented model (see figure 4.11). By contrast, in agriculture, technology effects appear much more likely, given the negative sign of the import penetration elasticity.

Economywide trade results must be interpreted with caution, as they are available for three divisions only and are only significant for employment share regressions. Nonetheless, it is doubtful whether other divisions producing largely non-traded goods (utilities, construction, most services) would have greater import penetration effects than those detected for the three divisions used in the analysis.

The case for pervasive trade effects is further weakened by estimating the technology and trade model separately for the high and low microeconomic reform periods. Results from both manufacturing and economywide data show import penetration elasticities being insignificant or having the wrong sign (respectively). By contrast, the strength of technology variable elasticities and export elasticities is robust to this sub-sampling exercise. Further, the strength of these elasticities is generally greater in the high reform period, which suggests that government measures designed to improve the operating environment of firms have caused them to reconsider their mix of skills, their export orientation, their use of technology, and/or provided flexibility to do all these things.

6 Conclusions

This paper set out to identify possible contributing factors to the changing earnings distribution in Australia by examining the changing demand for high skilled workers. It is argued that the relative increase in demand for high skilled workers has contributed to the earnings inequality observed in the economy. The effects of microeconomic reform on the demand for high skilled workers in the economy were also explored.

The focus of this paper is on exploring the role of SBTC on the changing demand for high skilled workers. The SBTC theory argues that the changing level of technology use has changed the nature of the demand for labour. Evidence of its existence has been reported across many industrialised countries. This hypothesis was first investigated using descriptive and decomposition analysis, and then more specifically through regression techniques.

The paper provides support for SBTC as an important factor in determining the relative demand for high skilled workers in the datasets and time frame examined. It also provides evidence that microeconomic reform played a role in this trend.

A Data sources and series construction

This appendix contains details of the data sources used in the paper. In addition, it presents an explanation of how the various series are constructed. Finally, it provides a brief overview of descriptive statistics on selected variables.

A.1 Industry classification concordance

The data used in this paper are classified according to the Australian and New Zealand Standard Industrial Classification (ANZSIC). This classification replaced the Australian Standard Industrial Classification (ASIC) in 1994-95 for the Labour Force Survey (LFS) and the Employee Earnings and Hours (EEH) survey.

ASIC data are reclassified to ANZSIC to create a time series for the period 1978–98. Due to the limited availability of data, this reclassification is based on a broad correspondence rather than precise concordances.[1]

Table A.1 provides the concordance used to reclassify the ASIC data into ANZSIC at the industry division level. Table A.2 provides the concordance used for the disaggregated manufacturing data.

[1] Generally, the data used in this paper are at the 2-digit subdivision level. Data are required at the 4-digit level for a precise concordance.

Table A.1 **ASIC/ANZSIC concordance for industry divisions**

ANZSIC classification	*Main corresponding ASIC sector(s)*[a]
A Agriculture, forestry and fishing	A Agriculture, forestry, fishing and hunting
B Mining	B Mining
C Manufacturing	C Manufacturing
D Electricity, gas and water supply	D Electricity, gas and water
E Construction	E Construction
F Wholesale trade	F Wholesale and retail trade (Wholesale subdivision only)
G Retail trade	F Wholesale and retail trade (Retail subdivision only)
H Accommodation, cafes and restaurants	L Recreation, personal and other services (Restaurants, hotels and clubs subdivision only)
I Transport and storage	G Transport and storage
J Communication services	H Communication
K, L Finance, insurance, property and business services	I Finance, property and business services
M Government administration and defence	J Public administration and defence
N, O Education, health and community services	K Community services
P Cultural and recreational services	L Recreation, personal and other services (Entertainment and recreational services subdivision only)
Q Personal and other services	L Recreation, personal and other services (Personal services and Private households employing staff subdivisions only)

a Although this correspondence is assumed to provide a reasonable basis for ascertaining broad industry trends, there are a number of individual activities that moved between sectors with the introduction of ANZSIC. Details of these moves are presented in ABS (1993a).

Source: Based on ABS (*Australian and New Zealand Standard Industrial Classification*, 1993 Edition, Cat. no. 1292.0).

Table A.2 **Manufacturing ANZSIC-based industry classification and correspondence to ASIC**

ANZSIC-based classification		*Main corresponding ASIC industry(s)*	
21	Food beverages and tobacco	21	Food beverages and tobacco
22	Textiles, clothing, footwear and leather	23	Textiles
		24	Clothing and footwear
		345	Leather and leather products
24	Printing, publishing and recorded media	26	Paper, paper products, printing and publishing
		less	263 Paper and paper products
25	Petroleum, coal, chemicals and associated products	27	Petroleum, coal, chemicals and associated products
		346	Rubber products
		347	Plastic and related products
Basic metal products		29	Basic metal products
271	Iron and steel manufacturing		
272	Basic non-ferrous metal manufacturing		
273	Non-ferrous basic metal product manufacturing		
Structural and sheet metal products		31	Fabricated metal products
274	Structural metal product manufacturing		
275	Sheet metal product manufacturing		
276	Fabricated metal product manufacturing		
Transport equipment		32	Transport equipment
281	Motor vehicle and part manufacturing		
282	Other transport equipment manufacturing		
Other manufacturing		Other manufacturing	
23	Wood and paper products	25	Wood, wood products and furniture
26	Non-metallic mineral products	28	Non-metallic mineral products
283	Photographic and scientific equipment manufacturing	33	Other machinery and equipment
284	Electronic equipment manufacturing	263	Paper and paper products
285	Electrical equipment and appliance manufacturing	34	Miscellaneous Manufacturing
		less	345Leather and leather products
286	Industrial machinery and equipment manufacturing	less	346Rubber products
		less	347Plastic and related products
29	Other manufacturing		

Source: Gretton and Fisher (1997).

A.2 Occupational concordance

The classification of occupations used by the ABS changed on two occasions between 1978 and 1998. In 1986, the Classification and Classified List of Occupations (CCLO) was replaced by the first edition of the Australian Standard Classification of Occupations (ASCO1). In 1996, this classification was in turn superseded by the second edition of the Australian Standard Classification of

Occupations (ASCO2). These changes mean that employment data series have to be concorded back to a common classification, in this case from CCLO and ASCO2 to ASCO1.

This concordance is performed using two ABS link files, which give a cross-tabulation of CCLO and ASCO1 (ABS cat. no. 2182.0) and ASCO1 and ASCO2 (ABS cat. no. 1232.0) frequencies in the 1986 and 1996 population censuses, respectively (see tables A3 and A4). Based on these link files, it is possible to allocate the population of one major group occupation in the 'source' classification to several other major group occupations in the 'destination' classification (eg 5 per cent of 'professionals, technical and related workers' in CCLO are allocated to ASCO1 'managers and administrators', 73 per cent to 'professionals', 17 per cent to 'para-professionals', etc.).

Table A.3 **CCLO-ASCO1 link file**

ASCO1 major groups as percentage of CCLO major groups

CCLO major group	Managers	Profs	Para-Profs	Trades pers.	Clerks	Personal	Plant ops	Laborers	NS[a]	Total
	ASCO1 major group									
Males										
Professional tech. & related	5.0	73.0	17.0	1.0	1.0	1.0	0.0	1.0	1.0	100.0
Admin., exec., managerial	68.0	4.0	4.0	4.0	5.0	10.0	2.0	2.0	2.0	100.0
Clerical workers	7.0	10.0	3.0	1.0	68.0	8.0	0.0	1.0	2.0	100.0
Sales workers	13.0	1.0	4.0	2.0	2.0	71.0	0.0	6.0	1.0	100.0
Farmers, fishers, etc.	59.0	0.0	2.0	15.0	0.0	0.0	3.0	21.0	0.0	100.0
Miners, quarrymen, etc.	1.0	1.0	4.0	5.0	0.0	0.0	55.0	32.0	2.0	100.0
Transport & comm.	3.0	1.0	6.0	1.0	9.0	4.0	69.0	7.0	1.0	100.0
Tradesmen, prod. process	2.0	2.0	3.0	51.0	1.0	0.0	14.0	25.0	2.0	100.0
Service, sport, recreation	3.0	2.0	19.0	15.0	1.0	12.0	5.0	40.0	1.0	100.0
Armed services	6.0	7.0	18.0	27.0	10.0	2.0	13.0	5.0	11.0	100.0
NS	7.0	5.0	5.0	11.0	5.0	1.0	12.0	23.0	31.0	100.0
Females										
Professional tech. & related	2.0	55.0	30.0	0.0	4.0	7.0	0.0	1.0	0.0	100.0
Admin., exec., managerial	52.0	6.0	2.0	2.0	16.0	15.0	0.0	2.0	4.0	100.0
Clerical workers	3.0	3.0	1.0	1.0	81.0	10.0	0.0	1.0	1.0	100.0
Sales workers	10.0	0.0	1.0	2.0	2.0	79.0	0.0	5.0	0.0	100.0
Farmers, fishers, etc.	70.0	0.0	0.0	5.0	1.0	0.0	0.0	18.0	4.0	100.0
Miners, quarrymen, etc.	3.0	15.0	8.0	0.0	11.0	14.0	8.0	39.0	3.0	100.0
Transport & comm.	4.0	2.0	2.0	1.0	59.0	5.0	22.0	6.0	1.0	100.0
Tradesmen, prod. process	1.0	1.0	1.0	12.0	2.0	1.0	33.0	46.0	2.0	100.0
Service, sport, recreation	2.0	2.0	2.0	14.0	2.0	30.0	1.0	48.0	1.0	100.0
Armed services	10.0	7.0	17.0	2.0	34.0	14.0	5.0	3.0	8.0	100.0
NS	5.0	3.0	4.0	4.0	12.0	13.0	8.0	23.0	28.0	100.0

	ASCO1 major group									
Persons										
Professional tech. & related	3.0	64.0	24.0	1.0	3.0	4.0	0.0	1.0	1.0	100.0
Admin., exec., managerial	66.0	4.0	4.0	3.0	6.0	11.0	2.0	2.0	3.0	100.0
CCLO major group	Mana gers	Profs	Para - Profs	Trades pers.	Clerks	Perso nal	Plant ops	Labor ers	NS[a]	Total
Clerical workers	4.0	4.0	1.0	1.0	78.0	9.0	0.0	1.0	1.0	100.0
Sales workers	12.0	1.0	3.0	2.0	2.0	75.0	0.0	5.0	1.0	100.0
Farmers, fishers, etc.	62.0	0.0	1.0	12.0	0.0	0.0	2.0	20.0	1.0	100.0
Miners, quarrymen, etc.	1.0	1.0	4.0	5.0	1.0	0.0	54.0	32.0	2.0	100.0
Transport & comm.	3.0	1.0	5.0	1.0	16.0	4.0	63.0	7.0	1.0	100.0
Tradesmen, prod. process	2.0	2.0	2.0	46.0	2.0	1.0	16.0	27.0	2.0	100.0
Service, sport, recreation	3.0	2.0	9.0	14.0	1.0	23.0	2.0	45.0	1.0	100.0
Armed services	7.0	7.0	18.0	25.0	12.0	3.0	13.0	5.0	10.0	100.0
NS	6.0	4.0	4.0	9.0	7.0	5.0	11.0	23.0	30.0	100.0

a NS = ‘not stated’ and ‘inadequately described’.

Source: ABS cat. no. 2182.0.

Table A.4 **ASCO2-ASCO1 link file**

ASCO1 major groups as a percentage of ASCO2 major groups

	ASCO1 major groups									
ASCO2 major groups	Managers	Profs	Para - Profs	Trades pers.	Clerks	Personal	Plant ops	Laborers	NS[a]	Total
Males										
Managers & admins	98.6	0.8	0.6	0.0	0.0	0.1	0.0	0.0	0.0	100.0
Proofs	2.2	86.6	6.9	0.4	0.0	4.0	0.0	0.0	0.0	100.0
Assoc. profs	28.3	1.1	38.5	7.6	5.3	16.3	1.4	1.1	0.5	100.0
Trades pers.	0.0	0.0	0.8	95.4	0.0	0.0	2.9	0.2	0.8	100.0
Advanced clerical	0.0	0.0	34.0	0.0	39.2	26.9	0.0	0.0	0.0	100.0
Int. clerical	0.2	1.3	6.7	0.0	42.4	45.3	0.0	4.2	0.0	100.0
Int. production	0.0	0.0	0.0	1.3	0.0	0.0	73.3	25.4	0.0	100.0
Elementary clerical	0.0	0.0	0.0	0.0	13.9	62.2	1.1	22.9	0.0	100.0
Labourers	0.3	0.0	0.0	0.4	0.0	0.3	2.2	96.8	0.0	100.0
NS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	100.0	100.0
Females										
Managers	94.8	1.3	3.1	0.0	0.0	0.8	0.0	0.0	0.0	100.0
Prof	1.2	72.6	24.6	0.4	0.0	1.2	0.0	0.0	0.0	100.0
Assoc. Prof	26.9	1.1	25.6	4.0	17.7	22.9	0.3	1.3	0.2	100.0
Trades	0.0	0.0	2.3	96.2	0.0	0.0	0.7	0.2	0.6	100.0
Advanced clerical	0.0	0.0	5.0	0.0	91.7	3.3	0.0	0.0	0.0	100.0
Int. clerical	0.1	0.5	1.3	0.0	56.8	37.3	0.0	3.9	0.0	100.0
Int. production	0.0	0.0	0.0	0.3	0.1	0.2	65.1	34.2	0.0	100.0
Elementary clerical	0.0	0.0	0.0	0.0	10.7	82.6	0.5	6.2	0.0	100.0
Labourers	0.2	0.0	0.0	0.1	0.0	0.4	1.5	97.8	0.0	100.0
NS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	99.9	100.0
Persons										
Managers	97.5	0.9	1.3	0.0	0.0	0.3	0.0	0.0	0.0	100.0
Prof	1.7	79.5	15.9	0.4	0.0	2.6	0.0	0.0	0.0	100.0
Assoc. Prof	27.8	1.1	33.3	6.1	10.3	19.0	0.9	1.2	0.4	100.0
Trades	0.0	0.0	1.0	95.4	0.0	0.0	2.7	0.2	0.8	100.0
Advanced clerical	0.0	0.0	8.3	0.0	85.8	5.9	0.0	0.0	0.0	100.0
Int. clerical	0.1	0.8	2.9	0.0	52.5	39.7	0.0	4.0	0.0	100.0
Int. production	0.0	0.0	0.0	1.2	0.0	0.1	72.0	26.8	0.0	100.0
Elementary clerical	0.0	0.0	0.0	0.0	11.8	75.6	0.7	11.9	0.0	100.0
Labourers	0.3	0.0	0.0	0.3	0.0	0.4	1.9	97.2	0.0	100.0
NS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	99.9	100.0

a NS = ‘not stated’ and ‘inadequately described’.

Source: ABS cat. no. 1232.0.

It should be noted that the concordance process outlined above is imperfect, for several reasons:

- Link files only exist at an economywide level or levels, not for individual industries. Their application to industry figures is therefore likely to cause structural breaks in employment by occupation by industry series.
- Link files are obtained by classifying workers according to two distinct classifications in the same population census. They therefore represent a snapshot of the overlap at the time of census taking. Inevitably, the nature of this overlap changes from one year to the next. However, the same link file has to be applied to data pertaining to several years.
- Link files measure classification overlap in census data. However, annual employment numbers used in this paper are based on different data, from the Labour Force Survey. This means that the application of the link file is likely to lead to a structural break in employment series for some occupations and some industries at the time of the change in classification.
- Link files are available for females, males and persons. However, these three link files are consistent only in the context of the census data from which they are calculated. When applied separately to Labour Force Survey data, inconsistencies appear due to differences in gender balances (over time and between industries). In this paper, gender inconsistencies are resolved by concording classifications separately for males and females, and then adding up numbers to form the persons series.
- Link files contain an 'N.S.' category denoting that a person's occupation could not be adequately determined from his or her answer. In the absence of information on the most likely occupational group of these respondents, they are removed from the analysis altogether. In the event that these removed observations are predominantly attached to non white collar high skilled workers, a bias is introduced into the analysis. However, given that number involved is low, this bias is likely to be negligible.

A.3 Employment

Data source

A reasonably consistent time series for the number employed (aged 15 years and over, in full and part-time employment) by occupation, gender and ANZSIC divisions is constructed for the period 1978 to 1998. Similarly, time series for ANZSIC-based manufacturing subdivisions are constructed for the same period.

These series are constructed using data from the Labour Force Survey microfiche for August of each year. For the manufacturing series, some unpublished data for industry groups are also used to create the time series (see table A.2).

Time series construction

Between 1978 and 1994, employment data are classified according to ASIC. The data preceding this are classified according to ANZSIC. To construct the time series, all ASIC data are reclassified to ANZSIC based on the industry concordance shown in tables A.1 and A.2.

ABS data for accommodation, restaurants and cafes, cultural and recreational services and personal and other services industries are available in ANZSIC from 1986. The ASIC subdivisions, libraries, museums and the arts (ASIC code 92) and other services (ASIC code 96) are subtracted from the education, health and community services industry to eliminate double counting due to the use of the ANZSIC backcast data. These estimates are used in conjunction with the broad ANZSIC industrial classification detailed in table A.2.

There are several changes in occupational classifications over the period 1978 to 1998. The occupational classification used in this paper to create the time series is based on ASCO1. As such, the CCLO data between 1978–85 are reclassified to ASCO1 according to the concordance outlined in table A.3. Similarly, ASCO2 data between 1996–98 are reclassified to ASCO1 following table A.4.

ASCO1 classifies occupations according to skill level and skill specialisation. The former is a function of the amount of formal education, on-the-job training and previous experience required before an individual can satisfactorily perform a particular set of tasks. The skill level of an occupation relates to the field of knowledge required, tools or equipment used, materials worked on and goods and services produced in relation to the tasks performed (Barnes et al. 1999).

ASCO1 divides the workforce into eight skill-based occupational groups. As mentioned in chapter 3, this paper aggregates the first three of these groupings to measure skilled employment — managers and administrators, professionals and para-professionals. Barnes et al. (1999) provides a broad definition of these groupings which is reproduced below (see ABS 1986 for a more detailed discussion).

- *Managers and administrators*: head government, industrial, agricultural, commercial and other establishments, organisations, or departments within the organisation. They determine policy and direct and coordinate the functioning of the establishment, organisation or department, usually through subordinate executives. Most occupations in this group have a level of skill equal to a three year degree and five to ten years experience in a relevant field or industry. Examples include parliamentarians, judges, general managers, production managers, farmers and farm managers, and shop managers.

- *Professionals*: perform analytical, conceptual and creative tasks requiring a high level of intellectual ability and a thorough understanding of an extensive body of theoretical knowledge. Most occupations in this group have a level of skill equal to a three year degree or diploma, with some occupations requiring a longer basic degree and/or postgraduate qualifications. Examples include natural scientists, engineers, medical practitioners, lawyers and accountants.
- *Para-professionals*: perform complex technical tasks requiring an understanding of a body of theoretical knowledge and significant practical skills. Occupations in this group have a level of skill equal to a two to three year para-professional certificate or associate diploma. Most para-professionals receive some on-the-job training in addition to formal education. Examples include medical and scientific technicians, pilots, nurses and police.

A.4 Total wage bill

Data source

A consistent time series is constructed for average weekly total earnings (AWE) by occupational classification and ANZSIC industry division for the period 1986 to 1998. AWE data are also available for ANZSIC manufacturing subdivisions. AWE data by occupation and industry are not available prior to 1986.

These data are obtained from the Survey of Employee Hours and Earnings for May of each year for all industries except Agriculture, forestry and fishing. Wage data for the latter are August data from the *Weekly Earnings of Employees (Distribution) Survey*.

Data construction

The ABS provided data on a consistent ANZSIC industry division and subdivision basis for the entire period. However, this series still required adjusting to be consistent with the ANZSIC industry classification detailed in tables A.1 and A.2. For the aggregated ANZSIC industry divisions — finance, insurance, property and business services and education, health and community services — employment weighted averages are used to calculate industry AWEs.

For manufacturing industry subdivisions, raw ABS data on AWEs are adjusted to match the modified ANZSIC classification used in this paper (table A.2). Specifically, employment weighted averages are used also to create a consistent time series for the ‘non-standard’ ANZSIC manufacturing subdivisions (basic metal products, fabricated metal products, transport equipment and other manufacturing).

AWE data for 1998 required special treatment because they are initially supplied in ASCO2 format by the ABS. Equivalent ASCO1 AWEs are obtained by taking an employment weighted average of ASCO2 AWEs, based on the previously mentioned ASCO1-ASCO2 1996 link file (see table A.4). Finally, missing 1997 data are inferred by assuming a constant discrete growth rate for each occupation (by industry) between 1996 and 1998.

After concording the data, the total wage bill is found by multiplying AWE by occupation and industry by the corresponding total employment figure in a given year. Because all wage bill figures enter the analysis as ratios, they are not deflated to constant dollar values.

A.5 Trade

Trade data used in this paper measure imports and exports of merchandise only and, as such, are only available for a limited number of divisions: divisions A, B, and C; all manufacturing subdivisions. The data are obtained from two separate sources:

- 1979–88: ABS cat. no. 5410.0; and
- 1989–98: ABS cat. no. 5464.0.

Data for the first period are available by ASIC industry and are therefore concorded to ANZSIC using the industry concordance described in tables A.1 and A.2. Three-digit level trade data required for the concordance of manufacturing subdivisions are obtained from EconData (Industry Commission Australian Manufacturing and Trade database).

Regarding the second period, trade data are available in both ASIC and ANZSIC format from 1989 to 1996. This makes it possible to reallocate — for that period only — the manufacturing subdivisions trade data to match the ‘modified’ ANZSIC classification used here (see table A.2). For the remainder of the period (1997–98), it is assumed that the weight of ‘modified’ ANZSIC subdivisions within ‘parent’ subdivisions (eg of ANZSIC 281 and 282 within ANZSIC 28) equals the 1994–96 average. This average is then used to derive missing data for 1997–98.

Finally, ABS data on merchandise imports and exports by industry in 1978 are missing and therefore backcasted using linear regression.

Once a complete and consistent ANZSIC series is available in current dollars for the period 1978–98, it is converted to constant 1989-90 dollar values using import and export price indices available from the EconData database (1978–96) and ABS cat. nos. 6405.0 and 6414.0 (exports and imports, respectively, 1997–98).

A.6 Capital stock

The various net capital stock (by type of asset) series for 1-digit level industries are obtained from unpublished ABS working estimates of chain volume measures. The reference year for the original series is 1997-98. To ensure consistency with other variables in the paper, these original chain volume measures are converted to 1989-90 values using the following steps:

1. Chain volume measures for each year are expressed as fractions of the 1989-90 measure; and
2. Fractions for each year are then multiplied by the current dollar value of net capital stock in 1989-90 (also available as unpublished working estimates from the ABS).

The procedure above is implemented for each type of asset and for each 1-digit level industry. Values for each type of asset are then added up to form the total net capital stock series.

Net capital stocks at the 2-digit manufacturing industry level are Productivity Commission estimates (Gretton and Fisher 1997, PC 1999) based on ABS data.

A.7 Value added

Gross value added figures for 1-digit level ANZSIC industries are obtained from the EconData database. These data are in the form of chain volume measures based on 1997-98 values. They are converted to 1989-90 values using the same procedure as described above in relation to net capital stocks:

1. Chain volume measures of value added in each year are expressed as fractions of the 1989-90 measure; and
2. Fractions for each year are then multiplied by the current dollar value of value added in 1989-90 (also available from EconData).

With respect to the 2-digit level industries forming the manufacturing division, value added figures used are Productivity Commission estimates (Gretton and Fisher 1997, PC 1999) based on ABS data.

A.8 Research and development

The following table summarises the research and development (R&D) data sources and availability.

There are several adjustments needed to the data as delivered. The industries reported for government and higher education are not consistent with those reported for businesses. The time periods covered by each source also vary. The detail for both manufacturing subdivisions and non-manufacturing industries is inconsistent. In the 1980s, the detail for non-manufacturing industries is reported every second year. The 1990s data provide much greater detail than prior periods for all three types of R&D.

Government and higher education R&D spending is reported by socio-economic objective and therefore does not necessarily provide information on specific industries. It is determined, given the sparsity of the government information, that it not be included in R&D values. For the higher education data, where it is clear which industry is associated with the spending, these monies are allocated to that industry. The remainder is left undistributed. This will have the impact of understating R&D spending activity associated with some industries. However, it is deemed preferable to understate when unsure, than to allocate across all industries on an arbitrary basis.

When detail is only available for every other year, the intervening year is interpolated. Detail of non-manufacturing breakdown for years prior to 1993 is based on the relationship between these industries' R&D spending in the 1980s and 1990s and total R&D spending. Ratios are calculated and applied to capture trends. Where no information is available, it is coded as missing values. Some other industry breakdown details are unavailable due to confidentiality reasons. These values are left undistributed. Given the uneven patterns of R&D spending, and the wide fluctuations between industries, if more than one year of data is missing, it is coded as a missing value.

The industry concordance is consistent with the methods outlined in section A.1 above. Finally, GDP price deflators are used to obtain constant 1989–90 values.

Table A.5 **R&D data sources and availability**[a]

Source	*Industry*	*Period Covered*
Business Expenditure on R&D by Industry		
	Mining	1974,1977,1979,1982,1984,1985-1998
	Manufacturing	1974,1977,1979,1982,1984,1985-1998
	Food, beverages and Tobacco	1974,1977,1979,1982,1984,1985-1998
	Textiles, clothing , footwear and leather	1974,1977,1979,1982,1984,1985-1998
	Wood and paper products	1974,1977,1979,1982,1984,1985-1998
	Printing, publishing and recorded media	1974,1977,1979,1982,1984,1985-1998
	Petroleum, coal, chemical & assoc.	1974,1977,1979,1982,1984,1985-1998
	Non-metallic mineral	1974,1977,1979,1982,1984,1985-1998
	Metal Product	1974,1977,1979,1982,1984,1985-1998
	Machinery and equipment	1974,1977,1979,1982,1984,1985-1998
	Other	1974,1977,1979,1982,1984,1985-1998
	Wholesale and retail trade	1974,1977,1979,1982,1985,1987,1989,1991-92
	Real estate and business services	1974,1977,1979
	Other industries	1974,1977,1979
	Finance, investment insurance and business services	1982,1984, ,1987,1989,1991-92
	Property and business services	1982,1984, ,1987,1989,1991-98
	Electricity, gas and water	1993-1998
	Construction	1993-1998
	Wholesale trade	1993-1998
	Retail trade	1993-1998
	Accommodation, café and restaurants	1993-1998
	Transport and storage	1993-1998
	Communication services	1993-1998
	Finance and insurance	1993-1998
	Property and business services	1993-1998
	Government	1993-1998
	Education	1993-1998
	Health and Community services	1993-1998
	Cultural and recreational services	1993-1998
	Personal and other services	1993-1998
Higher Education Organisations R&D Expenditure by Source of Funds[b]		
	Agriculture, forestry and Fishing	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Mining	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Manufacturing	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Construction	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Energy	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Transport	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Communications	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Health	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Education	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998
	Welfare	1978,1981,1984,1986,1988,1998
	Community Services	1978,1981,1984,1986,1988,1990,1992,1994,1996,1998

Table A.5 **R&D data sources and availability[a] (continued)**

Source	*Industry*	*Period Covered*
General Government R&D Expenditure by Source of Funds[b]		
	Agriculture, forestry and Fishing	1991,1993,1995,1997
	Mining	1991,1993,1995,1997
	Manufacturing	1991,1993,1995,1997
	Construction	1991,1993,1995,1997
	Energy	1991,1993,1995,1997
	Transport	1991,1993,1995,1997
	Communications	1991,1993,1995,1997
	Health	1991,1993,1995,1997
	Education	1991,1993,1995,1997
	Welfare	1991,1993,1995,1997
	Social and Community development	1991,1993,1995,1997

a ASIC data reported for data prior to 1992. ASIC-ANZSIC industry concordance outlined earlier in this appendix is used to construct the time series. **b** Only relevant industries listed.

Source: Unpublished ABS data.

A.9 Descriptive statistics for selected variables

From the time series discussed above, a number of derived variables are constructed:

- share of high skilled workers in employment;
- share of high skilled workers in the total wage bill;
- ratio of R&D expenditure to value added ('R&D intensity');
- ratio of net capital stock to value added ('overall capital intensity');
- ratio of machinery and equipment to value added ('M&E intensity');
- ratio of buildings and structures to value added ('B&S intensity');
- ratio of software to value added ('software intensity');
- ratio of merchandise imports to valued added ('import penetration'); and
- ratio of merchandise exports to value added ('export intensity').

Summary descriptive statistics for these derived variables are presented in table A.6. A salient feature of that table is the fact that high skilled workers command a smaller share of employment and the total wage bill in manufacturing subdivisions than economywide (divisions). In terms of use of technology, manufacturing is more R&D intensive than other industries, while the reverse is true for overall capital intensity. Within the overall capital stock, buildings and structures play a more important part in divisions than in manufacturing. Finally, divisions are more export oriented and less subject to import competition than manufacturing subdivisions.

The eight subdivisions making up the manufacturing sector tend to be more homogeneous than other parts of the economy in respect to their skill intensity, as reflected in lower standard deviation figures, relative to the mean. This is also true of their overall capital intensity, while divisions display less variability than subdivisions in regard to their R&D intensity.

Table A.6 **Summary statistics**

Calculated from pooled time series-cross section annual data for 1978–98[a]

	Mean	*Standard deviation*	*Minimum*	*Maximum*	*n*
Divisions (includes manufacturing division)					
Share of high skilled workers in employment	0.289	0.151	0.109	0.668	315
Share of high skilled workers in wage bill	0.379	0.169	0.145	0.729	195
R&D intensity	0.005	0.006	0.00008	0.039	280
Overall capital intensity	2.518	1.859	0.584	9.006	315
M&E intensity	0.672	0.366	0.178	2.082	315
B&S intensity	1.829	1.686	0.248	7.534	315
Software intensity	0.017	0.020	0.000	0.107	315
Import penetration[b]	0.349	0.388	0.024	1.302	63
Export intensity[b]	0.619	0.206	0.334	1.058	63
Manufacturing subdivisions					
Share of high skilled workers in employment	0.177	0.050	0.089	0.330	168
Share of high skilled workers in wage bill	0.268	0.099	0.130	0.476	104
R&D intensity	0.019	0.030	0.0003	0.152	168
Overall capital intensity	1.038	0.416	0.305	2.429	168
M&E intensity	0.656	0.247	0.141	1.445	168
B&S intensity	0.382	0.223	0.137	0.985	168
Import penetration	0.689	0.505	0.121	2.165	168
Export intensity	0.491	0.474	0.015	2.201	168

a 1986–98 for the wage bill share. **b** Data based on three divisions only: agriculture, mining and manufacturing.

Source: Commission estimates based on ABS data detailed in this appendix.

B Decomposition analysis

This appendix complements and extends the decomposition analysis results presented in chapter 4 in a number of ways. First, it explains the methodology used to decompose the change in the share of high skilled workers into shifts between industries and changes within industries, and to decompose the latter by gender (section B.1). Second, it provides measures of the contribution made by each sector and industry to the economywide total, between and within effects (section B.2). Third, it presents measures of the contribution made by each industry to the gender effects by sector (section B.3).

B.1 Decomposition methodology

The standard method[1] for decomposing the aggregate change in the share of high skilled workers (ΔP) into between-industry and within-industry (for *i* = 1, … *N* industries) effects is as follows:

$$\Delta P = \sum_i \Delta Si\overline{P}i + \sum_i \Delta Pi\overline{S}i \qquad \text{(B.1)}$$

where P_i = high $\text{skilled}_i/E_i$, is the share of high skilled workers employed in industry *i* and $S_i = E_i/E_{TOT}$ is the share of employment in industry *i* in total employment. A bar over a variable indicates an average of the start and end period value, thereby isolating the contribution of the change in either one of the two variables to the aggregate change. Therefore, the first term on the right-hand side of the equation shows the change in the total share of high skilled workers due to employment shifts *between* industries with different shares of these workers (industry shares of high skilled workers are held fixed). This term is referred to as the ‘between’ effect and is interpreted as a reflection of trade effects. The second term represents the change in the aggregate share attributable to changes in the share of high skilled workers *within* each industry (industry employment shares are held fixed). This is referred to as the ‘within’ effect and is thought to measure the extent of skill biased technical change (SBTC).

[1] For example, see Berman et al. (1994), Machin (1995) and Machin and Van Reenen (1998).

The standard within-between decomposition described above provides the starting point for the gender decomposition. During that next step, the within effect obtained previously is decomposed further, as illustrated in the expression below:

$$\Delta P = \sum_i \Delta S_i \overline{P}_i + \sum_i \Delta S_i^M \overline{P}_i^M \overline{S}_i + \sum_i \Delta P_i^M \overline{S}_i^M \overline{S}_i + \sum_i \Delta S_i^F \overline{P}_i^F \overline{S}_i + \sum_i \Delta P_i^F \overline{S}_i^F \overline{S}_i \qquad \text{(B.2)}$$

In equation (B.2), ΔP, S_i, and P_i are as previously defined, and the *M* and *F* superscripted variables are defined as follows:

S_i^M = share of males in industry *i*'s workforce;

S_i^F = share of females in industry *i*'s workforce;

P_i^M = proportion of males in high skilled occupations in industry *i*; and

P_i^F = proportion of females in high skilled occupations in industry *i*.

The first term on the right hand side of equation (B.2) measures the between-industry effect. The sum of terms two to five measures the within-industry effect. The second and fourth terms measure the contribution to the within effect of a change in the share of males and females, respectively, in each industry. The sum of these two terms is referred to as a 'net share effect'.[2]

The third and fifth terms measure the contribution to the within effect of a change in the proportion of males and females, respectively, with high skilled occupations in each industry. These skill upgrading effects are henceforth referred to as 'upskilling' effects.

B.2 Sector and industry contributions to economywide effects

Table B.1 is a more detailed version of table 4.1 in that it shows the contribution each of the four economic sectors makes to the economywide between, within and total effects. For each type of effect, the sectoral contributions sum up to the economywide figure. It should be noted that these results do not say anything about the actual change in high skilled employment for each sector individually (which is

2 By definition, a positive male share effect implies a negative female share effect, albeit not necessarily of the same magnitude.

addressed in section 4.2 in the text), only about the contribution they make to the aggregate change.[3]

Table B.1 **Sectoral contributions[a] to economywide changes in the share of high skilled employment,[b] 1978–98**

Annualised percentage point change

	1978–85	*1986–98*
All industries (economywide changes)		
Total	0.30	0.29
Between	0.18	0.06
Within	0.12	0.23
Sectoral contributions to economywide changes		
Primary		
Total	0.01	-0.10
Between	0.00	-0.07
Within	0.01	-0.03
Manufacturing		
Total	-0.05	0.01
Between	-0.08	-0.05
Within	0.03	0.06
Utilities and construction		
Total	0.01	0.01
Between	-0.02	-0.02
Within	0.03	0.03
Services		
Total	0.33	0.37
Between	0.27	0.20
Within	0.06	0.17

a These are the sectoral contributions relevant to table 4.1. **b** Employment data are for August of each year.

Source: Commission estimates from unpublished ABS *Labur Force Survey* data.

The results in table B.1 show that the services sector made the largest contribution to the total increase in high skilled employment between 1978 and 1998. The relatively large ‘between’ component for services in both subperiods reflects the reallocation of employment to the services sector. In the latter period, within-industry effects in services, and to a lesser extent manufacturing and utilities and construction, also made significant contributions to skill upgrading in the economy.

3 For instance, a sector may make a large contribution to economywide upskilling despite experiencing relatively low within-sector upskilling. This may be the case if that sector accounts for a large proportion of total employment.

The picture provided by table B.1 may be refined further by examining the industry contributions to the economywide effects. These results are presented in table B.2 for the two subperiods.

Table B.2 **Industry contributions to the total, between and within effects[a,b]**
Annualised percentage point change

	Employment shares (1978–85)				*Employment shares (1986–98)*			
Industry division	*Rank[c]*	*Total*	*Within*	*Between*	*Rank[c]*	*Total*	*Within*	*Between*
Finance, property and business services	1	0.16	0.05	0.10	1	0.30	0.15	0.14
Education, health and community services	2	0.13	-0.03	0.16	4	0.02	-0.03	0.04
Cultural and recreational services	3	0.02	0.01	0.02	7	0.01	-0.01	0.02
Communication	4	0.02	0.02	0.00	11	0.00	0.00	-0.01
Transport and storage	5	0.02	0.01	0.00	12	-0.01	0.01	-0.01
Electricity, gas and water	6	0.01	0.01	0.01	14	-0.01	0.02	-0.03
Mining	7	0.01	0.01	0.01	10	0.00	0.00	-0.01
Wholesale trade	8	0.01	0.01	0.00	6	0.01	0.01	0.00
Personal and other services	9	0.01	0.01	0.00	5	0.02	0.00	0.02
Accommodation, cafes and restaurants	10	0.01	0.00	0.00	2	0.02	0.00	0.02
Agriculture, forestry and fishing	11	0.00	0.00	0.00	15	-0.09	-0.04	-0.06
Construction	12	0.00	0.02	-0.02	3	0.02	0.02	0.00
Retail trade	13	-0.01	0.02	-0.03	13	-0.01	-0.01	0.01
Government administration and defence	14	-0.02	-0.03	0.01	8	0.01	0.03	-0.02
Manufacturing	15	-0.05	0.03	-0.08	9	0.01	0.06	-0.05
All industries		**0.30**	**0.12**	**0.18**		**0.29**	**0.23**	**0.06**

a These are the industry contributions relevant to table 4.1. **b** In some instances, the between and within effects do not sum to the total. This is due to rounding to the second decimal place. **c** Industries are ranked in descending order of contribution to the total employment effect (third and seventh columns).

Source: Commission estimates from unpublished *ABS Labour Force Survey* data.

The salient feature of table B.2 is the importance of the finance, property and business services sector for skill upgrading in the economy. In both subperiods, this industry provided the largest contribution to the overall effect: in excess of 50 per cent in 1978–85 and in excess of 100 per cent in 1986–98. In the first subperiod, this industry's contribution was mainly in the form of a between effect, showing it gained from the reallocation of employment.[4] In the latter period, however, the

4 The share of high skilled workers in the finance, property and business services industries averaged around 40 per cent during 1978–98 — compared to the average for all industries of

within effect dominated, reflecting upskilling taking place within the finance, property and business services industry itself (in addition to continuing reallocation of employment to it).

The other major contributor to economywide upskilling in the first period — education, health and community services — dropped away considerably in the second period. Indeed, no industry except finance contributed more than 0.02 percentage points to the overall effect (0.29 percentage points) in the second period.

Finally, it may be noted that the industries which contributed to economywide deskilling in both periods (that is, had a negative total contribution), generally did so *via* a negative between effect. The only exceptions are government administration and defence in 1978–85 and retail and agriculture, forestry and fishing in 1986–98.

In table B.3, the same exercise as in table B.2 is repeated at the sectoral level. That is, the contribution of each industry to the change in the employment share of high skilled workers in the sector is calculated and ranked. This approach makes for a better picture of the changes occurring within a particular sector, especially in the case of manufacturing where that sector is disaggregated down to the subdivision level.

In manufacturing, one of the major contributors to sectoral skill upgrading is petroleum, coal, chemicals and associated products. By itself, this industry accounted for between a quarter and over one half of the total sectoral effect. While its contribution was evenly divided between the within and between effects in 1978–85, the within effect was dominant by far during 1986–98. Indeed, with a few exceptions, within-industry skill upgrading effects were considerably stronger during the second period in most manufacturing subdivisions, leading to a quadrupling of the overall manufacturing within effect.

In contrast to the petroleum industry, the printing, publishing and recorded media industry did not maintain its high ranking from the earlier to the latter period. While its share of high skilled workers rose strongly during 1986–98, this was offset by its falling share of total employment. The basic metal products industry followed an opposite trend, rising from sixth to first place on the strength of its skill upgrading and rising share of employment.

30 per cent. Over this period, the employment share of this industry increased by 7 per cent, while it fell for most industries in the primary, manufacturing and utilities and construction sectors (that typically have lower shares of high skilled workers). This reallocation of employment to a sector with a relatively high need for high skilled workers has therefore contributed positively to the aggregate change in high skilled workers.

Table B.3 Industry contributions to the total, between and within effects of each sector[a,b]

Annualised percentage point change

Sector / Industry division	Employment shares (1978–85) Rank[c]	Contrib	Within	Between	Employment shares (1986–98) Rank	Total	Within	Between
Primary sector		**-0.04**	**0.10**	**-0.14**		**-0.42**	**-0.46**	**0.04**
Mining	1	0.15	0.09	0.06	1	0.05	0.07	-0.03
Agriculture, forestry and fishing	2	-0.19	0.01	-0.20	2	-0.47	-0.54	0.07
Manufacturing		**0.14**	**0.11**	**0.03**		**0.41**	**0.40**	**0.01**
Petroleum, coal, chemicals and associated products	1	0.08	0.04	0.04	2	0.11	0.10	0.01
Printing, publishing and recorded media	2	0.07	0.01	0.06	6	0.02	0.06	-0.04
Fabricated metal products	3	0.02	0.01	0.01	5	0.02	0.05	-0.03
Food, Beverage and Tobacco	4	0.02	0.03	-0.01	3	0.07	0.07	0.00
Textiles, clothing, footwear and leather	5	0.01	0.02	-0.01	7	0.02	-0.01	0.03
Basic metal products	6	-0.01	0.00	-0.01	1	0.15	0.13	0.02
Other manufacturing	7	-0.02	0.02	-0.03	4	0.04	0.01	0.03
Transport equipment	8	-0.03	-0.01	-0.02	8	-0.02	-0.01	-0.01
Utilities and construction		**0.32**	**0.26**	**0.06**		**0.25**	**0.40**	**-0.15**
Electricity, gas and water	1	0.21	0.07	0.13	2	-0.08	0.20	-0.28
Construction	2	0.12	0.19	-0.07	1	0.32	0.20	0.12
Services		**0.23**	**0.10**	**0.13**		**0.29**	**0.23**	**0.06**
Finance, property and business services	1	0.20	0.08	0.12	1	0.38	0.22	0.16
Education, health and community services	2	0.07	-0.05	0.12	10	-0.07	-0.04	-0.04
Communication	3	0.03	0.03	0.00	7	-0.01	0.00	-0.01
Cultural and recreational services	4	0.03	0.01	0.02	4	0.01	-0.01	0.02
Transport and storage	5	0.01	0.02	-0.01	8	-0.02	0.01	-0.03
Personal and other services	6	0.01	0.01	0.00	3	0.01	0.00	0.01
Accommodation, cafes and restaurants	7	0.00	0.01	-0.01	2	0.03	0.01	0.02
Wholesale trade	8	0.00	0.01	-0.02	5	0.00	0.02	-0.02
Retail trade	9	-0.06	0.03	-0.08	9	-0.03	-0.02	-0.01
Government administration and defence	10	-0.06	-0.05	-0.01	6	0.00	0.05	-0.05

a These are the industry contributions relevant to table 4.2. **b** In some instances, the between and within effects do not sum to the total. This is due to rounding to the second decimal place. **c** Industries are ranked in descending order of contribution to the total sectoral employment effects (third and seventh columns).

Source: Commission estimates from unpublished *ABS Labour Force Survey* data.

Not unexpectedly in the light of the results in table B.2, the finance, property and business services industry is the largest source of skill upgrading in the services sector as well as economywide, in both periods. Also of interest in that sector, the accommodation, cafes and restaurants industry rose from seventh to second position between the two periods. This reversal was entirely due to the fact that its share of sectoral employment rose in 1986–98, while it had been falling during 1978–85.

In utilities and construction, the downsizing carried out in the electricity, gas and water industry during the high microeconomic reform period (see box 3.2) is reflected in the negative between effect recorded in 1986–98. At the same time as this industry was upskilling rapidly during 1986–98, its share of total employment fell significantly, leading to a negative overall contribution to skill upgrading in the services sector.

Finally, in the primary sector, the fall in the share of high skilled workers in the agriculture, forestry and fishing industry between 1986–98 made the largest contribution to the consistently negative effect that industry had on sectoral skill upgrading. In contrast, the increased share of high skilled workers in the mining industry made a positive contribution to the within component of the sectoral change in both subperiods.

B.3 Industry contributions to the sectoral gender effects

Results of the industry contributions to the sectoral gender effects are reported in tables B.4 and B.5. Measures of the total, between and within effects pertaining to each of the four sectors remain the same as shown in table B.3. Each sector is now examined in turn. Measures of the net share, male upskilling and female upskilling effects are the same as those reported in table 4.3. Salient features of tables B.4 and B.5 are summarised below.

In agriculture, forestry and fishing, the very rapid within-industry deskilling which occurred in 1986–98 was due to both males and females deskilling at fairly similar rates. By contrast, in mining, upskilling was primarily a male phenomenon (in both periods).

In manufacturing, the strong overall contribution of the petroleum, coal, chemical and associated products industry in both periods was underlined by an acceleration of male and female upskilling. The spectacular improvement in the contribution of the basic metal products industry between the first and second periods was largely

Table B.4 **Industry contributions to the total, between, within and gender effects by sector[a,b] — 1978–85**

Annualised percentage point change

		Employment shares (1978–85)					
Sector / Industry division	*Rank[c]*	*Contrib*	*Within*	*(of which)*			*Between*
				Net share	*Male upskilling*	*Female upskilling*	
Primary sector		**-0.04**	**0.10**	**0.04**	**0.04**	**0.02**	**-0.14**
Mining	1	0.15	0.09	0.00	0.09	0.00	0.06
Agriculture, forestry and fishing	2	-0.19	0.01	0.04	-0.05	0.02	-0.20
Manufacturing		**0.14**	**0.11**	**-0.01**	**0.07**	**0.05**	**0.03**
Petroleum, coal, chemicals and associated products	1	0.08	0.04	0.01	0.01	0.01	0.04
Printing, publishing and recorded media	2	0.07	0.01	-0.01	0.00	0.02	0.06
Fabricated metal Products	3	0.02	0.01	0.00	0.01	0.00	0.01
Food, beverage and tobacco	4	0.02	0.03	-0.01	0.03	0.00	-0.01
Textiles, clothing, footwear and leather	5	0.01	0.02	0.00	-0.01	0.02	-0.01
Basic metal products	6	-0.01	0.00	0.00	0.01	-0.01	-0.01
Other manufacturing	7	-0.02	0.02	0.00	0.02	-0.01	-0.03
Transport equipment	8	-0.03	-0.01	0.00	-0.01	0.00	-0.02
Utilities and construction		**0.32**	**0.26**	**-0.02**	**0.26**	**0.02**	**0.06**
Electricity, gas and water supply	1	0.21	0.07	0.00	0.07	0.01	0.13
Construction	2	0.12	0.19	-0.02	0.20	0.01	-0.07
Services		**0.23**	**0.10**	**-0.02**	**0.08**	**0.04**	**0.13**
Finance, property and business services	1	0.20	0.08	0.01	0.04	0.04	0.12
Education, health and community services	2	0.07	-0.05	0.00	0.00	-0.05	0.12
Communication	3	0.03	0.03	0.00	0.03	0.00	0.00
Cultural and recreational services	4	0.03	0.01	0.00	0.00	0.01	0.02
Transport and storage	5	0.01	0.02	0.00	0.02	0.00	-0.01
Personal and other services	6	0.01	0.01	0.01	0.00	0.00	0.00
Accommodation, cafes and restaurants	7	0.00	0.01	0.00	0.00	0.01	-0.01
Wholesale trade	8	0.00	0.01	0.00	0.01	0.01	-0.02
Retail trade	9	-0.06	0.03	-0.01	0.02	0.02	-0.08
Government administration and defence	10	-0.06	-0.05	-0.01	-0.03	0.00	-0.01

a These are the industry contributions relevant to table 4.3. **b** In some instances, the between and within effects do not sum to the total. This is due to rounding to the second decimal place. **c** Industries are ranked in descending order of contribution to the total sectoral employment effect (third column).

Source: Commission estimates from unpublished *ABS Labour Force Survey* data.

Table B.5 **Industry contributions to the total, between, within and gender effects by sector[a,b] — 1986–98**

Annualised percentage point change

Sector / Industry division	Rank[c]	Employment shares (1986–98) Contrib	Within	(of which) Net share	Male upskilling	Female upskilling	Between
Primary sector		**-0.42**	**-0.46**	**-0.02**	**-0.15**	**-0.29**	**0.04**
Mining	1	0.05	0.07	0.00	0.07	0.01	-0.03
Agriculture, forestry and fishing	2	-0.47	-0.54	-0.02	-0.22	-0.30	0.07
Manufacturing		**0.41**	**0.40**	**0.01**	**0.20**	**0.19**	**0.01**
Basic metal products	1	0.15	0.13	0.01	0.08	0.05	0.02
Petroleum, coal, chemicals and associated products	2	0.11	0.10	0.00	0.05	0.04	0.01
Food, beverage and tobacco	3	0.07	0.07	-0.01	0.05	0.03	0.00
Other manufacturing	4	0.04	0.01	0.00	0.00	0.01	0.03
Fabricated metal Products	5	0.02	0.05	0.00	0.04	0.01	-0.03
Printing, publishing and recorded media	6	0.02	0.06	0.00	0.01	0.04	-0.04
Textiles, clothing, footwear and leather	7	0.02	-0.01	0.00	-0.02	0.01	0.03
Transport equipment	8	-0.02	-0.01	0.00	0.00	0.00	-0.01
Utilities and construction		**0.25**	**0.40**	**-0.02**	**0.30**	**0.12**	**-0.15**
Construction	1	0.32	0.20	0.00	0.12	0.08	0.12
Electricity, gas and water supply	2	-0.08	0.20	-0.01	0.17	0.04	-0.28
Services		**0.29**	**0.23**	**-0.03**	**0.09**	**0.17**	**0.06**
Finance, property and business services	1	0.38	0.22	0.00	0.09	0.12	0.16
Accommodation, cafes and restaurants	2	0.03	0.01	0.00	0.01	0.00	0.02
Personal and other services	3	0.01	0.00	0.00	-0.01	0.01	0.01
Cultural and recreational services	4	0.01	-0.01	0.00	-0.01	0.00	0.02
Wholesale trade	5	0.00	0.02	0.00	0.01	0.01	-0.02
Government administration and defence	6	0.00	0.05	-0.01	0.03	0.03	-0.05
Communication	7	-0.01	0.00	0.00	0.00	0.00	-0.01
Transport and storage	8	-0.02	0.01	0.00	0.01	0.00	-0.03
Retail trade	9	-0.03	-0.02	0.00	-0.02	0.01	-0.01
Education, health and community services	10	-0.07	-0.04	-0.02	-0.01	0.00	-0.04

a These are the industry contributions relevant to table 3.3. **b** In some instances, the between and within effects do not sum to the total. This is due to rounding to the second decimal place. **c** Industries are ranked in descending order of contribution to the total sectoral employment effect (third column).

Source: Commission estimates from unpublished *ABS Labour Force Survey* data.

due to a marked increase in upskilling by both genders in the second period. There was a decline in the contribution of the printing, publishing and recorded media industry.

Between the two periods occurred in spite of very rapid upskilling by females in the second period. Among the industries that contributed to sectoral deskilling in both periods, both male and female deskilling occurred in the first period, while only male deskilling existed in the second period (in textiles, clothing, footwear and leather).

Both the electricity, gas and water and construction industries experienced rapid upskilling in both periods. This was mainly underwritten by male upskilling, however, especially in the construction industry between 1978 and 1985.

In the services sector, the driving role of the finances, property and business services industry was strongly supported by upskilling by both genders. However, the rapid rate of female upskilling in that industry in 1986–98 is especially notable, accounting for over 40 per cent of the total skill upgrading in the services sector (0.12 out of 0.29). Among the industries that decreased in importance between the two periods, the decline in education, health and community services was partly due to a fall in the proportion of males, combined with deskilling by this gender. This is in contrast to the first period, where deskilling was entirely the preserve of females.

C Theoretical framework

In this appendix, the theoretical and methodological foundations underlying the analysis presented in chapter 5 are presented and discussed.

C.1 Derivation of estimating equations

If the SBTC hypothesis is a good explanation of changes in the demand for high skilled workers, it should be possible to show that cost-minimising producers use proportionately more high skilled labour the more advanced their production technology. Based on this premise, most studies investigating the occurrence of SBTC at the industry or establishment level have sought to estimate equations derived from a firm's cost function. By far the favoured functional form found in the literature is a restricted translog function for the total labour cost of a firm or an industry (for example Berman et al. 1994, Machin 1995, Machin and Van Reenen 1998, Haskel and Heden 1999). The translog function is a second order (or quadratic) Taylor's series approximation in logarithms to any unspecified cost function. This function has several advantages over other functional forms, which include the following.

- The translog cost function places very few restrictions on the underlying production technology. For instance, substitution elasticities between factors do not have to be constant (as in a CES production function) or equal to 1 (as in a Cobb-Douglas production function).
- The translog cost function can be estimated in a 'restricted' form. That is, the determinants of the total labour cost can be estimated at fixed or quasi-fixed quantities of the other inputs (capital, intermediate inputs). Put differently, producers are assumed to minimise labour costs under constrained levels of output, capital, other inputs and environmental variables such as technology. Hence, an added benefit of estimating a restricted form of the translog cost function is that no information on the price of other inputs is required. In economic terms, this is equivalent to estimating a short run total labour cost function.

Given *n* types of labour (j = 1, 2, …n) and *m* environmental variables (k = 1, 2, …m) the restricted total labour cost (TLC) of industry *i* can be expressed as:

$$TLC_i = f[\boldsymbol{w_{ij}}, K_i, Y_i, \boldsymbol{Z_{ik}}] \qquad \text{(C.1)}$$

where $\boldsymbol{w_{ij}}$ = vector of wages of n categories of workers;

K_i = real capital stock of industry i;

Y_i = real value added of industry i; and

$\boldsymbol{Z_{ik}}$ = vector of m environmental variables.

or, in translog form (suppressing the i subscript):

$$\ln TLC = \alpha_0 + \sum_{j=1}^{n} \alpha_j \ln w_j + \alpha_Y \ln Y + \alpha_K \ln K + \frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{n} \alpha_{jk} \ln w_j \ln w_k$$

$$+ \sum_{j=1}^{n} \alpha_{jK} \ln w_j \ln K + \sum_{j=1}^{n} \alpha_{jY} \ln w_j \ln Y + \frac{1}{2}\alpha_{YY} (\ln Y)^2$$

$$+ \frac{1}{2}\alpha_{KK} (\ln K)^2 + \phi(w, K, Y, Z) \qquad \text{(C.2)}$$

where

$$\phi(w, K, Y, Z) = \sum_{k=1}^{m} \delta_k Z_k + \sum_{k=1}^{m}\sum_{j=1}^{n} \lambda_{kj} \ln(w_j) Z_k + \sum_{k=1}^{m} \xi_k \ln(Y) Z_k + \sum_{k=1}^{m} \psi_k \ln(K) Z_k$$

$$+ \frac{1}{2}\sum_{k=1}^{m} \gamma_k (Z_k)^2$$

It can be shown that cost minimisation by producers requires that the share of each type of labour in total labour cost be equated with the first partial derivative of the cost function with respect to that type of labour's wage:

$$\frac{\partial \ln TLC}{\partial \ln w_j} = S_j \qquad \text{(C.3)}$$

with S_j = share of labour type j in total labour cost

Assuming only two types of labour, high skilled and lower skilled (j = h, l) — receiving wages equal to w_h and w_l respectively — and only one environmental variable — an index of the stock of technology denoted by TECH — yields the following equation for the share of high skilled labour in the total labour cost of industry *i*.[1]

$$S_h = \alpha_h + \alpha_{hY} \ln Y + \alpha_{hK} \ln K + \alpha_{hh} \ln w_h + \alpha_{hl} \ln w_l + \lambda_{hh} TECH \tag{C.4}$$

Note that the derivation of the above equation assumes that the parameters of the cost function are symmetric, that is:

$$\alpha_{ij} = \alpha_{ji} \tag{C.5}$$

Assuming homogeneity of degree one in prices implies that equation (C.4) can be rewritten as:

$$S_h = \alpha_h + \alpha_{hY} \ln Y + \alpha_{hK} \ln K + \alpha_{hh} \ln\left(\frac{w_h}{w_l}\right) + \lambda_{hh} TECH \tag{C.6}$$

Assuming constant returns to scale (CRS) implies that equation (C.6) can be rewritten as:

$$S_h = \alpha_h + \alpha_{hY} \ln\left(\frac{K}{Y}\right) + \alpha_{hh} \ln\left(\frac{w_h}{w_l}\right) + \lambda_{hh} TECH \tag{C.7}$$

In the SBTC literature, estimating equations based on equations (C.6) and (C.7) have been frequently used to investigate the effects of technological change on the relative demand for high skilled and lower skilled labour.[2] While changes in the dependent variable — the wage bill share of high skilled workers — are technically the net result of changes in relative quantities and relative wages, they can be

---

[1] With only two categories of labour, the equation for the share of lower skilled labour is redundant.

[2] For example, see Berman et al. 1993, 1994, Machin 1995, Machin et al. 1996, Machin and Van Reenen 1998, Haskel and Heden 1999.

legitimately regarded as reflecting demand shifts for different categories of workers, as long as the elasticity of substitution between the categories equals 1 (Autor et al. 1998).

Strengthening this interpretation of the share variable as indicative of demand shifts, it can be shown that the employment share is a non-linear transformation of the wage bill share if relative wages are constant across industries (see Bartel and Lichtenberg 1987). This is what is routinely assumed in most studies to date (for example, Berman et al. 1994), leading to the relative wage term on the right hand side being dropped.[3] Relative wages by industry are then assumed to move in unison over time, in response to macroeconomic shocks or cycles. In some cases, time dummies are introduced into the estimating equation to capture these common influences.

In general in the literature, the use of employment shares instead of wage bill shares as a dependent variable has led to qualitatively similar results.

Another adjustment to the estimating equation concerns the measurement of the technology variable. As the stock of technology in use by an industry or a firm is rarely observable and/or measurable, proxies are typically used. The choice of proxy, in the literature and in this paper, is discussed in chapter 3 (in particular, see box 3.3). As mentioned in that chapter, the variable of choice to use as proxy for the TECH variable has been R&D intensity.[4] While R&D expenditure is an important input into the generation of new technologies, it does not constitute technological change *per se*. The two variables may be expected to be fairly closely correlated, however.

The capital variable is also frequently used to indicate whether there is any complementary relationship between high skilled labour and technological advances which may be embodied in new capital stock. This avenue of technological change is an important one given that R&D by some firms or industries can spillover and be adopted by another part of the economy. Thus, even industries with no R&D such as accommodation, cafes and restaurants are able to incorporate technological advances into their production process. This is illustrated by the fact that, in that industry, the proportion of employees using computers rose from 13 per cent in 1994 to 17 per cent in 1998.

[3] In addition, in the wage bill share equation, the relative wage term adds bias due to the definitional relationship between the dependent variable and the relative wage measure.

[4] More specifically, R&D intensity is defined in this paper as BERD plus privately funded higher education R&D as a share of value added.

In this paper, the embodied technology argument is investigated more precisely by disaggregating the capital stock into three components: buildings and structures, machinery and equipment and software (the latter in division data only).

Given the adjustments to the theoretical framework discussed above, the equations to be estimated are as follows (using the aggregated capital stock for exposition purposes):

$$S_{it} = \beta_0 + \beta_1 \ln Y_{it} + \beta_2 \ln K_{it} + \beta_3 \ln\left(\frac{R\,\&\,D_{it}}{Y_{it}}\right) + \varepsilon_{it} \tag{C.8}$$

or, assuming constant returns to scale (CRS):

$$S_{it} = \beta_0 + \beta_1 \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_2\left(\frac{R\,\&\,D_{it}}{Y_{it}}\right) + \varepsilon_{it} \tag{C.9}$$

where S_{it} = share of high skilled workers in industry *i*'s wage bill (or employment);

K_{it} = real capital stock of industry *i*;

Y_{it} = real value added of industry *i*; and

$R\&D_{it}$ = real expenditure on R&D in industry *i*.

Now that the estimating equations have been established, it is necessary to determine the appropriate estimating procedure. This process is outlined in the next section.

C.2 Approaches to estimation

Given that the primary goal is to test the SBTC hypothesis, the interest is in the sign and significance of β_2 and β_3 in equation (C.8) and β_1 and β_2 in equation (C.9). A positive and significant coefficient on the R&D variable would reflect the within-industry upskilling effects of technological change. This would in turn provide evidence of SBTC in that particular industry. A positive coefficient on the capital (or capital intensity) variable would also be regarded as indirect evidence of SBTC. This is because it would reflect a complementary relationship between capital and high skilled labour. This would also reflect technological change–skill complementarity under the assumption of embodied technological progress.

One approach to estimating these equations is to apply ordinary least squares on pooled time series–cross section data. This has advantages both in terms of degrees of freedom and the explanatory power of the data. However, if the regression omits relevant variables from the right hand side of the equation, OLS estimates will no longer be the best linear unbiased estimates. There is reason to believe this will be the case with these equations. Environmental variables (observed and unobserved) which may strongly influence the proportion of high skilled workers in employment are not explicitly captured in this model. For instance, it has been suggested that the degree of unionisation of an industry is a negative influence on the share of high skilled workers in employment. As industries naturally differ with respect to unionisation, omitting this variable would mean the industry specific effect of unionisation is picked up by the error term, and the error term would have a non-zero mean. Furthermore, if the omitted variable is correlated with one of the right hand side variables in the equation, the error term will be correlated with it as well.

Virtually all SBTC studies using industry level data report significant industry-specific effects.[5] Thus, there is reason to suspect that omitted variable bias would affect OLS estimates based on pooled data. An alternative fortunately exists in the application of panel data techniques. Such techniques have been developed to account for unobserved individual and/or time heterogeneity in regressions based on data sets with both time and cross-sectional dimensions.[6] The basic premise of these models is that the effects of missing (and unknown) variables can be threefold: individual-specific and time-invariant; time-specific and individual-invariant; and individual and time-specific.

Moreover, panel data techniques have benefits beyond controlling for these types of omitted variables. Panel data are often more informative, allow for more variability, more degrees of freedom and more efficiency. Thus, their use reduces the risk of obtaining perverse or spurious results from regressing a single cross section or time series. Panel data also permit a more comprehensive examination of the dynamics of adjustment by allowing for a time element within a cross sectional framework. Cross sectional distributions that look relatively stable can hide a multitude of changes in the time dimension. Panel data sets have their difficulties and limitations as well. These include identifying and modelling the effects of unobserved heterogeneity. Also, the standard methods of estimating panel data (fixed and random effects models) impose constancy on the estimated coefficients across the entire panel.

[5] These effects have been handled in a variety of ways from differencing the estimated equation and applying weighted OLS (Machin and Van Reenen 1998) to applying industry specific dummies (Machin 1995).

[6] Readers interested in obtaining more information on these techniques are referred to Greene (2000) and Baltagi (1999).

A seemingly unrelated regressions (SUR) approach is less restrictive than panel data techniques in terms of the constraints imposed on the coefficients.[7] If the contemporaneous errors across industries are correlated with the dependent variable and the coefficients vary across industries within the panel, SUR would be a more appropriate technique compared with fixed or random effects models. Further, efficiency gains in the estimation of industry specific coefficients may be achieved by 'stacking' the regressions as a SUR does, rather than estimating separate OLS regressions for each industry. In the SUR framework, both intercepts and slope coefficients are free to differ between industries, thus picking up any differences in the average skill intensity (differences in intercepts) and in the impact of technology across industries (differences in slope coefficients).

In order to determine which is the appropriate method to apply to the data set, a test for constancy across industries of the β coefficients in equations (C.8) and (C.9) is applied. As mentioned, primary interest lies with β_2 and β_3 in (C.8) and β_1 and β_2 in (C.9). A significant test statistic rejecting the null hypothesis of equal coefficients indicates the necessity of allowing individual slope coefficients to differ in the estimation process, through a SUR model or a panel data technique such as random coefficients (Hildreth-Houck). If the null cannot be rejected, a joint estimation procedure is appropriate and a traditional panel technique is warranted.

The three types of effects in a panel setting (individual-specific and time-invariant, time-specific and individual-invariant, and individual and time-specific) can be modelled as fixed or random.

In a fixed effects model, the effects of the omitted variables are treated as fixed constants. The argument is that the effects of omitted variables, whatever their exact nature, can be absorbed into the intercept term of the regression as a means of explicitly allowing for the unobserved individual and/or time heterogeneity contained in the temporal cross sectional data. In other words, industry or time differences are captured by permanent differences in the intercepts of the estimated regressions.

The industry fixed effects model is estimated with industry dummies. That is, equations (C.8) and (C.9) become (ignoring fixed time and fixed individual & time effects):

$$S_{it} = D_i\alpha_i + \beta_1 \ln Y_{it} + \beta_2 \ln K_{it} + \beta_3 \ln\left(\frac{R\&D_{it}}{Y_{it}}\right)_{it} + \varepsilon_{it} \qquad \text{(C.10)}$$

[7] See footnote 6.

$$S_{it} = D_i\alpha_i + \beta_1 \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_2 \ln\left(\frac{R\,\&\,D_{it}}{Y_{it}}\right) + \varepsilon_{it} \tag{C.11}$$

where D_i = dummy variable taking the value 1 for industry i, 0 otherwise.

In this approach, any industry fixed and time invariant effects due to the existence of unobserved variables is captured by changes in the value of the coefficient α_i.

The alternative to a fixed effects model is a random effects model. This approach treats the individual-specific or time-specific effects as independent random disturbances around a mean industry specific effect (the intercept). The random effects representation of equations (C.8) and (C.9) is:

$$S_{it} = \alpha + \beta_1 \ln Y_{it} + \beta_2 \ln K_{it} + \beta_3 \ln\left(\frac{R\,\&\,D_{it}}{Y_{it}}\right)_{it} + v_i + \varepsilon_{it} \tag{C.12}$$

$$S_{it} = \alpha + \beta_1 \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_2 \ln\left(\frac{R\,\&\,D_{it}}{Y_{it}}\right) + v_i + \varepsilon_{it} \tag{C.13}$$

where v_i is a random disturbance associated with industry i.

Though it is not technically a test of fixed versus random effects, the Hausman (1978) test can provide some guidance when choosing between the two models. It is based on the null hypothesis that error terms and explanatory variables are uncorrelated, in which case a random effects model is preferred. If the alternative hypothesis of correlation between the error terms and explanatory variables cannot be rejected, the random effects model is not appropriate and a fixed effects model may be used instead.

Another consideration influencing the choice of one model over another is whether the data to be analysed are exhaustive of an entire population or in the nature of a sample. If the latter, random effects are generally considered preferable (Greene 2000). Given the differing degree of homogeneity of the division and subdivision data highlighted in appendix A (section A.9), it may be expected a priori that the random effects model would fit the former best and the fixed effects model the latter.

If the null hypothesis of constancy among the coefficients is rejected, then neither the fixed nor the random effects model is suitable, and, as discussed, SUR is preferred. This technique allows variation in coefficient estimates yet incorporates commonality in the data when estimating these coefficients.[8] The system of equations estimated using SUR would then become (using equation C.9 as an example):

$$
\begin{aligned}
S_{1t} &= \beta_{01} + \beta_{11} \ln\left(\frac{K_{1t}}{Y_{1t}}\right) + \beta_{21}\left(\frac{R\&D_{1t}}{Y_{1t}}\right) + \varepsilon_{1t} \\
S_{2t} &= \beta_{02} + \beta_{12} \ln\left(\frac{K_{2t}}{Y_{2t}}\right) + \beta_{22}\left(\frac{R\&D_{2t}}{Y_{2t}}\right) + \varepsilon_{2t} \\
&\vdots \\
S_{nt} &= \beta_{0n} + \beta_{1n} \ln\left(\frac{K_{nt}}{Y_{nt}}\right) + \beta_{2n}\left(\frac{R\&D_{nt}}{Y_{nt}}\right) + \varepsilon_{nt}
\end{aligned}
\tag{C.14}
$$

8 SUR suffers from a reduction in degrees of freedom and possible over-specification over pooling techniques. Thus alternative specifications including random coefficients were also applied. The results are inferior to those obtained using SUR.

D Detailed econometric results*

As described in chapter 5 and in more detail in appendix C, two procedures are used to estimate the model — panel and seemingly unrelated regressions (SUR).[1] The first step in making a determination between the two techniques is to test specifically for constancy in the coefficient estimates on capital and technology. A significant test statistic rejecting the null hypothesis of equal coefficients indicates the need to allow individual slope coefficients to differ in the estimation process, ie a SUR model. If the null cannot be rejected, a joint estimation of a single coefficient is appropriate and a more traditional panel, fixed or random effects, method can be applied.

This appendix will present the results for testing for the appropriate model and provide details of the results reported in chapter 5. Manufacturing will be examined first, followed by the division, or economywide dataset.

D.1 Manufacturing

The manufacturing data set was tested to determine the constancy of coefficient estimates. The null hypothesis that the beta coefficients (on both the capital and technology variables) from equations C.10 to C.13 are equal cannot be rejected at the 5 per cent level using a chi-squared test. In addition, correlation in the error term across individual industries was detected. Therefore, a traditional panel effects model is applied for the manufacturing data set.

Once panel techniques are deemed appropriate, it was then to be determined whether a fixed or random effect model should be used. A consideration influencing the choice of one model over another is whether the data to be analysed are exhaustive of an entire population or in the nature of a sample. If the latter, random effects are generally considered preferable (Greene 2000). However, a priori the fixed effects model would appear to be more appropriate given the greater degree of homogeneity already detected in the data.

* We wish to particularly thank Dr. Mark Harris for his detailed comments on this aspect of the project. Any remaining errors are our own.

[1] For more information on panel data and SUR techniques see, for example, Greene (2000) and Baltagi (1999).

Main Results

The fixed and random effects models are used to estimate equations (C.10) to (C.13), with the share variable representing either an employment or a wage bill share. The equations represent the constant returns to scale (CRS) and non-constant returns to scale (NCRS) versions of the model. Following the international literature, results are presented using an aggregate measure of capital stock (table D.1). The disaggregated capital results, separating machinery and equipment (M&E) from building and structures (B&S), are presented in table D.2.

Table D.1 **Results[a] of fixed and random effects estimation for manufacturing using aggregate capital stock**

Standard error in brackets

	Dependent variable			
Explanatory variable[c]	*Employment share*		*Wage bill share*	
Model[b]	*CRS*	*NCRS*	*CRS*	*NCRS*
Random effects				
ln(v)		0.009 (0.021)		-0.025 (0.039)
ln(k)		0.061* (0.011)		0.124* (0.027)
ln(kv)	0.059* (0.012)		0.124* (0.027)	
rdv	0.276* (0.116)	0.275* (0.111)	0.752* (0.254)	0.516 (0.254)
Wald χ^2	28.09*	49.17*	28.92	33.78*
Hausman test	3.67	7.95*	26.5*	8.35*
	CRS	NCRS	CRS	NCRS
Fixed effects				
ln(v)		0.015 (0.021)		-0.052 (0.040)
ln(k)		0.067* (0.012)		0.159* (0.027)
ln(kv)	0.065* (0.012)		0.140* (0.027)	
rdv	0.303* (0.118)	0.296* (0.111)	0.866* (0.255)	0.697* (0.252)
F statistic	10.5*	13.98*	17.94*	15.74*

a Results reported * significant at 5% level and # significant at 10% level. **b** CRS = constant returns to scale. NCRS = non-constant returns to scale. **c** ln(kv) = log of capital intensity, ln(v) = log of value added, ln(k) = log of capital stock, rdv = R&D intensity.

Source: Commission estimates based on data set detailed in appendix A.

It would appear these explanatory variables provide a good fit when estimating shares of high skilled workers (significant F and Wald test statistics) and that the fixed effect model is preferred over the random effects (significant Hausman test), as shown in table D.1. First, the Wald and F test statistics represent a joint test of the set of linear constraints in the respective regressions. With the exception of the CRS wage bill equation, the test statistics are all significant at the 5 per cent level. This indicates that the explanatory variables do a good job in estimating the relative demand for high skilled workers. Second, the Hausman test is applied to the random effect model, testing the null hypothesis that the effects are indeed random. This null is rejected at the 5 per cent level in all but one instance (CRS employment shares). It would then appear that the a priori assumptions are correct and the fixed effects model is, in general, preferable for manufacturing.

Looking at the results of the fixed effects model, strong support for SBTC in the manufacturing sector is found. The R&D intensity variable is always positive and always significant in both sets of equations, across both employment and wage bill shares. The relationship between capital (or capital intensity) and the proportion of high skilled workers is also always significant and positive.

Table D.2 **Disaggregated capital regressions — manufacturing[a]**

Standard errors in brackets

Explanatory variable[b]	Dependent variable: Employment shares (1978–98) CRS		Employment shares (1978–98) NCRS		Wage bill shares (1986-98) CRS		Wage bill shares (1986-98) NCRS	
rdv	0.171	(0.134)	0.299*	(0.129)	0.562#	(0.308)	0.683*	(0.300)
ln(M&E)			0.026*	(0.012)			0.091*	(0.037)
ln(B&S)			0.051*	(0.024)			0.083	(0.054)
ln(v)			0.017	(0.022)			-0.049	(0.040)
ln(M&E/Y)	0.046*	(0.012)			0.132*	(0.035)		
ln(B&S/Y)	0.001	(0.023)			-0.007	(0.044)		
F statistic		12.7*		12.1*		8.15*		11.02*

a Employment and wage bill share regressions are based on 8 manufacturing subdivisions panel data. The panel data are for the 1978–98 in the case of employment shares, while wage bill data are available for the period 1986–98. Fixed effects models are used. * significant at 5 per cent or higher. # significant at 10 per cent level. **b** ln(M&E) = log of machinery and equipment, ln(M&E/Y) = log of M&E intensity, ln(B&S) = log of building and structures and ln(B&S/Y) = log of B&S intensity. All other variables are as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

The results from the capital by asset type regressions are reported in table D.2. Here, the results of the fixed effects model are presented. They confirm the argument (presented in chapters 3 and 4) that skill complementarity is better captured through the machinery and equipment variable rather than the buildings and structures variable. The positive and significant relationship between the share of high skilled workers and R&D intensity is maintained when the capital variable is broken down by asset type. The positive and significant relationship for M&E provided continuing support for the SBTC hypothesis under the assumption of embodied technological change.

Trade–augmented model

Following Machin et al. (1996), imports and exports as a share of value added are added separately to the right hand side of the specification. The trade hypothesis postulates that there is a positive relationship between the share of high skilled workers and the level of imports. An extension of the trade hypothesis states that higher exports may increase the demand for high skilled workers further (see chapter 3 and Berman et al. 1994 for a further explanation of trade effects).

Table D.3 **International trade and disaggregated capital regressions — manufacturing**[a]

Standard errors in brackets

	Dependent variable							
Explanatory variable[b]	*Employment shares (1978–98)*				*Wage bill shares (1986-98)*			
	CRS		*NCRS*		*CRS*		*NCRS*	
rdv	-0.051	(0.122)	0.063	(0.120)	0.132	(0.324)	0.268	(0.329)
ln(M&E)			0.002	(0.012)			0.050	(0.038)
ln(B&S)			0.067*	(0.022)			0.078	(0.052)
ln(v)			0.009	(0.019)			-0.047	(0.039)
ln(M&E/Y)	0.016	(0.012)			0.066#	(0.037)		
ln(B&S/Y)	0.026	(0.020)			0.025	(0.043)		
ln(X/Y)	0.028*	(0.007)	0.029*	(0.006)	0.029#	(0.016)	0.026#	(0.016)
ln(I/Y)	0.018#	(0.010)	0.010	(0.010)	0.016	(0.022)	0.011	(0.022)
F statistic		11.4*		10.24*		14.5*		16.24*

a Employment and wage bill share regressions are based on 8 manufacturing subdivisions. The data are for the 1978–98 in the case of employment shares, while wage bill data are available for the period 1986–98. Fixed effects models are used for manufacturing. * significant at 5 per cent or higher. # significant at 10 per cent level. **b** ln(X/Y) = log of exports per value added, ln(I/Y) = log of imports per value added, all other variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

Results from this model provide little support for the trade explanation for the changing demand for high skilled workers. The import coefficient is insignificant in all cases aside from the CRS employment share regression, where it is significant at the 10 per cent level. The results of this regression show the share of exports in value added as the major factor influencing the demand for high skilled workers in manufacturing. This suggests that, on average, exported manufactured goods require high skilled labour for their production. This may reflect the increasing need for producers to implement ‘best practice’ production processes in order to compete successfully on international markets.[2]

2 However, it should be noted that the link between export propensity and competition has not been clearly established (Machin and Van Reenen 1998).

R&D intensity is no longer significant when the trade variables are added to the estimating equation. In most cases, machinery and equipment also becomes insignificant — the exception being the wage bill share regression with CRS. This may be due to the fact that the impact of technology is entirely captured in the export component of the estimating equation.

The fastest growing segment of manufacturing exports is ‘other manufacturing’. As shown in appendix A, this category includes industries such as photographic and scientific equipment, electronic equipment and industrial machinery and equipment. All of these manufacturing processes utilise relatively advanced manufacturing techniques compared with more traditional sectors such as food, beverage and tobacco. Thus, the positive and significant coefficient on the export variable (in lieu of R&D intensity) is not necessarily a rejection of SBTC. Rather is could be seen as a further enhancement to the embodied technology argument.

Microeconomic reform

As discussed in chapter 3, the acceleration of microeconomic reform in Australia since the mid-1980s has most likely affected firms’ optimal input combination (PC 1999). For this reason, it is important that the low and high reform periods be identified in the data set when regressing employment shares.[3] One method is to flag the high reform period using a dummy variable. Unfortunately, the beginning of the extensive microeconomic reform period (1986) coincides with a structural break in the employment series, due to a change in the occupational classification system. A dummy variable would therefore pick up both the effects of microeconomic reform and those of the concordance break.[4] An alternative is to split the data into low (1978–85) and high (1986–98) reform periods, and to re-estimate the employment share models on the basis of each sub-sample.[5]

The results of this exercise for the fixed effects model are presented in table D.4. Again, only the fixed effects model outcomes are presented.

[3] Wage data are only available for 1986–98 so this exercise cannot be replicated in terms of the wage bill share.

[4] Indeed, a dummy variable is already used to capture the effects of the concordance break for the employment regressions run over the entire period, 1978–98.

[5] For a discussion of the choice of low and high reform period, see chapter 3 (box 3.2).

Table D.4 **Panel estimation[a] of low and high reform period (employment shares) — manufacturing**

Standard errors in brackets

Explanatory *variable[b]*	*Low reform period*		*High reform period*	
	CRS	*NCRS*	*CRS*	*NCRS*
rdv	-0.926# (0.519)	-0.864 (0.513)	-0.034 (0.231)	0.053 (0.236)
ln(M&E)		0.040* (0.021)		0.053* (0.027)
ln(B&S)		0.023 (0.033)		0.015 (0.037)
ln(v)		-0.003 (0.033)		-0.016 (0.028)
ln(M&E/Y)	0.047* (0.021)		0.064* (0.026)	
ln(B&S/Y)	-0.009 (0.026)		-0.018 (0.031)	
ln(X/Y)	0.011 (0.009)	0.011 (0.008)	0.027* (0.011)	0.025* (0.011)
ln(I/Y)	0.015 (0.015)	0.018 (0.015)	0.013 (0.015)	0.009 (0.015)
F statistic	2.99*	2.96*	15.43*	13.49*

a* significant at the 5% level, # at the 10% level. **b** All variables as previously defined.

Source: Commission estimates based on data set described in Appendix A.

From table D.4, the contrast between the low and high reform periods is most apparent where the impact of the export variable is concerned. Export intensity is highly significant and positive the high reform period, while it is insignificant in the earlier period. This suggests that the significance of the coefficient for the entire period (as shown in table D.3) was driven by the performance of the high reform years. With respect to the complementarity of the high skilled share with capital (stock or intensity), it is detected in results for both periods. However, the size of the M&E coefficients shows that this effect has increased in the latter period. When the sample is split into the two periods, the weakly significant import intensity variable (table D.3) drops out. This further weakens any support for the trade hypothesis.

These results highlight the change in the impact of technology on the demand for high skilled labour following the acceleration of microeconomic reform in the mid-1980s. The impact of technological change appears to have been indirect in the low reform period, taking place solely through additions to the capital stock and limited R&D spillovers. In the high reform period, the role of the capital stock is complemented by that of export intensity, possibly reflecting the 'opening up' of the Australian economy (potentially underwritten by government policy).[6]

[6] It is interesting to note the results of this exercise without including the trade variables. A strong shift in the significant of the rdv coefficient is found. In the low reform period, the sign is negative and the coefficient insignificant. In the high reform period, the parameter is positive and highly significant. This bolsters support for the contention that export intensity is capturing the technological change affect.

D.2 Economywide

Main model

Using the same chi-squared test applied in the manufacturing dataset, the null hypothesis of constancy among the coefficients was rejected for divisions. This result is not surprising. Imposing the same slope coefficient on the technology variables, for example, is making the implicit assumption that technology affects all industries in the same way. For example, a 1 per cent increase in R&D intensity has the same effect on the proportion of high skilled workers employed in mining as it does in finance, property and business services. Given the degree of heterogeneity of the division data, such a homogeneous impact is unlikely — which was borne out by test statistics. Therefore, this dataset calls for an econometric technique that allows variation in coefficient estimates yet incorporates commonality in the data when estimating these coefficients, namely a SUR.[7]

SURs estimate on an equation by equation basis and hence, they are very flexible. They can also be inefficient in the sense of estimating many parameters. However, SURS allow these 'separate' equations to be treated as a system by allowing a correlation in their error terms. Indeed, the Breusch-Pagan test statistic for correlation in error terms is significant (see tables D.5 and D.6) for both estimating equations (CRS v NCRS) as well as for both dependent variables (employment v wage bill share). Given that the gain in efficiency in using SUR over OLS increases directly with the correlation of the disturbance terms, this result reconfirms the choice of estimating procedures.

Again, for comparability with the international literature, results are presented using measures of aggregate capital stock. These results are reported in tables D.5 (CRS model) and D.6 (NCRS model). The results for the disaggregated model, separating out M&E, B&S and software, are presented in table D.7. Here, to save space, only the CRS version is presented.

7 SUR suffers from a reduction in degrees of freedom and possible over-specification over pooling techniques. Thus alternative specifications including random coefficients were also applied. The results are inferior to those obtained using SUR.

Table D.5 **Results[a] of SUR estimation of CRS model — divisions**
Standard error in brackets

Industry / Explanatory variable[d]	Employment share[b] *ln(kv)*	Employment share[b] *rdv*	Wage bill share[c] *ln(kv)*	Wage bill share[c] *rdv*
Mining	-0.022 (0.031)	1.758* (0.882)		
Manufacturing	0.089* (0.025)	1.416* (0.255)	0.217* (0.016)	1.906* (0.228)
EGW			-0.557* (0.052)	3.695* (0.635)
Construction	-0.018 (0.017)	13.234* (2.981)	-0.112* (0.028)	31.301* (4.086)
Wholesale	0.023 (0.019)	2.677* (1.202)		
Retail	0.124* (0.034)	-19.388* (2.322)	0.209* (0.028)	-30.480* (2.518)
Transport	-0.032* (0.016)	58.536* (9.779)	-0.094* (0.019)	54.065* (13.102)
Communication	-0.045* (0.023)	11.082* (3.918)	-0.071* (0.022)	16.789* (2.784)
Finance	-0.171* (0.064)	12.866* (2.308)	-0.198* (0.034)	18.514* (1.879)
Government			-0.683* (0.039)	169.323* (29.197)
Education/Health	0.072* (0.027)	1.646* (0.844)	-0.078* (0.024)	3.010* (0.400)
Cultural			0.192* (0.054)	-152.92* (17.071)
Breusch-Pagan Test		99.62*		77.78#

a Results are reported only for those industries for which the coefficient on *rdv* is significant. * = significant at the 5 per cent level. # =significant at the 10 per cent level. **b** Accommodation and Personal services divisions have been dropped due to missing observations. **c** Agriculture, Accommodation and Personal services divisions have been dropped due to missing observations. **d** All variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

As shown in tables D.5 and D.6, the majority of industries examined have significant and positive coefficients for the technology parameter. Technology has a negative impact on the proportion of high skilled workers in the retail and cultural industries (as well as mining in the NCRS model). At the same time, the capital intensity coefficient is positive in these industries. This may reflect the fact that installed capital requires high skilled personnel, while the introduction of new technologies is done as a high skilled labour saving technique.

For the CRS model, significant negative coefficients for the capital intensity variables are found in the majority of industries. When comparing the results of the capital intensity variable with the capital variable, three things become apparent. First, the capital intensity variable is significant more often than capital, in both the employment and wage bill share equations. Second, it is more often negative than capital. Third, it has smaller standard errors. This may be interpreted as firms which use more machinery to produce output use this machinery as a labour saving device, and that capital intensity is a good measure of such a strategy.

Table D.6 **Results[a] of SUR estimation of NCRS model — divisions**
Standard error in brackets

	Dependent variable					
Explanatory variable[d]	*Employment share[b]*			*Wage bill share[c]*		
Industry	*ln(k)*	*ln(v)*	*rdv*	*ln(k)*	*ln(v)*	*rdv*
Mining						-2.11* (1.11)
Manufacturing	0.167* (0.02)		0.518* (0.23)	0.297* (0.04)	-0.141* (0.04)	0.585* (0.26)
EGW	-0.60* (0.108)	0.623* (0.07)		0.632* (0.21)	0.305* (0.07)	6.53* (0.79)
Construction		0.04* (0.014)	11.06* (2.21)		0.151* (0.03)	18.24* (2.85)
Wholesale				0.287* (0.15)		
Retail	0.132* (0.04)	-0.143* (0.04)	-15.93* (3.7)	0.308* (0.03)	-0.492* (0.03)	-5.07* (2.45)
Transport	0.112* (0.05)		54.21* (9.5)	0.351* (0.11)	-0.06# (0.03)	81.92* (8.13)
Communications		0.11# (0.07)	12.36* (3.7)	-0.339* (0.09)	0.227* (0.06)	13.75* (2.28)
Finance	-0.28* (0.04)	0.517* (0.05)	4.15* (1.45)	-0.241* (0.04)	0.495* (0.05)	3.79* (1.67)
Government				-0.357* (0.12)	0.541* (0.07)	108.4* (36.2)
Education/Health						4.011* (0.37)
Cultural			-66.85* (34)	0.395* (0.12)	-0.494* (0.24)	-196.3* (41.4)
Breusch-Pagan Test			92.6#			88.38*

a Results are reported only for those industries for which the coefficient on *rdv* is significant. * = significant at the 5 per cent level. # =significant at the 10 per cent level. **b** Accommodation and Personal services divisions have been dropped due to missing observations. **c** Agriculture, Accommodation and Personal services divisions have been dropped due to missing observations. **d** All variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

The negative sign of the coefficient for capital intensity does not completely invalidate the SBTC hypothesis, only that part which posits capital-skill complementarity. Even that conclusion may be premature since the capital stock variable includes buildings and structures as well as equipment.

The results of SUR estimation of the model incorporating capital by asset type are given in table D.7. For succinctness, only the CRS model results are presented. Some divisions are left out of the estimation because they had missing observations (agriculture, accommodation, personal services).

From these results, a number of observations can be made. First, both M&E and software are a significant influence in the majority of industries represented in the sample. However, when significant, machinery and equipment is only positive around fifty per cent of the time. This supports the belief that firms have employed M&E as a labour saving measure. By contrast, software is generally positive. In manufacturing, for instance, software is shown to be the driving force in capital–skill complementarity. Here, software is significant and positive in both equations while M&E is significantly negative in both. In the equivalent regression presented in section D.1.1 (see table D.2), M&E per value added is significant in both the employment and wage bill equations. This implies that this significant result is being driven by the software component of capital spending and further illustrates the need to understand what type of capital investment is driving the changing demand for labour.

Table D.7 Results[a] of SUR estimation with disaggregated capital — divisions

Standard error in brackets

	Dependent variable							
	Employment share[b]				Wage bill share[c]			
Explanatory variable[d]	*ln(B&S/Y)*	*ln(M&E/Y)*	*ln(Soft/Y)*	*rdv*	*ln(B&S/Y)*	*ln(M&E/Y)*	*ln(Soft/Y)*	*rdv*
Industry division								
Agriculture	-0.149*	0.117#	-0.020*	7.010*				
	(0.070)	(0.070)	(0.004)	(3.179)				
Mining	0.218*	-0.301*	0.018*	-2.024	0.126	-0.227	0.026#	-2.149
	(0.110)	(0.141)	(0.008)	(1.511)	(0.131)	(0.159)	(0.014)	(1.772)
Manufacturing	0.0039	0.044	0.010*	0.968*	0.031	0.080	0.031*	-0.424
	(0.027)	(0.027)	(0.004)	(0.324)	(0.047)	(0.058)	(0.006)	(0.441)
EGW	-0.141	-0.110*	0.015	3.328	0.380*	-0.003	0.093*	8.835*
	(0.192)	(0.038)	(0.010)	(2.428)	(0.182)	(0.049)	(0.017)	(1.390)
Construction	-0.014	-0.047#	0.013*	7.847*	0.089*	-0.333*	0.022*	19.187*
	(-0.016)	(0.024)	(0.002)	(1.519)	(0.015)	(0.028)	(0.002)	(1.504)
Wholesale	-0.035	0.061*	-0.002	4.636*	-0.312	0.380#	0.032	-0.568
	(0.034)	(0.027)	(0.005)	(1.373)	(0.190)	(0.229)	(0.021)	(4.230)
Retail	0.034	0.188*	-0.005	-22.124*	0.166*	0.441*	-0.016*	-27.357*
	(0.024)	(0.041)	(0.003)	(2.341)	(0.051)	(0.072)	(0.007)	(6.867)
Transport & storage	-0.156*	0.102*	-0.004	57.092*	-0.405*	0.265*	-0.013	79.852*
	(0.060)	(0.042)	(0.004)	(10.304)	(0.139)	(0.101)	(0.010)	(19.343)
Communication	0.047	0.062	0.023*	7.310*	0.064	-0.163*	0.050*	12.245*
	(0.029)	(0.042)	(0.008)	(4.371)	(0.043)	(0.053)	(0.018)	(4.280)
Finance	-0.277*	-0.145*	0.071*	-0.437	-0.386*	0.123	0.055*	1.622
	(0.029)	(0.034)	(0.008)	(1.324)	(0.062)	(0.092)	(0.011)	(1.560)
Government	-0.447*	0.153*	-0.035*	-7.398	-0.299*	-0.270*	0.062*	61.406#
	(0.052)	(0.028)	(0.009)	(32.820)	(0.109)	(0.111)	(0.029)	(35.755)
Education	0.062	0.029	-0.003	1.215#	-0.324*	0.045*	-0.039*	2.941*
	(0.060)	(0.020)	(0.006)	(0.687)	(0.066)	(0.012)	(0.008)	(0.516)
Cultural services	0.012	-0.180*	0.023*	-43.951	0.054	0.234	-0.031	-133.84*
	(0.099)	(0.088)	(0.010)	(30.075)	(0.146)	(0.151)	(0.023)	(37.270)

a Results are reported only for those industries for which the coefficient on at least one of the selected explanatory variables is significant. * = significant at the 5 per cent level. # = significant at the 10 per cent level. **b** Accommodation and personal Services have been dropped due to missing observations. **c** Agriculture, accommodation and personal Services have been dropped due to missing observations. **d** ln(Soft/Y) = log of software per value added. All other variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

Second, the influence of buildings and structures is less significant than that of other assets, overall, and usually negative when significant. Thus, there is some confirmation of the suspicion that a number of the results observed in the capital variable in the previous chapter are due to the aggregation level of the capital stock. Agriculture, wholesale, transport, finance, government and education all show significant negative coefficients for the building and structure variable. Among these divisions, only finance continues to show a significant negative coefficient on the machinery and equipment variable.

Finally, the mainly positive and significant effects of R&D intensity on the two share variables, already detected in the SUR regressions presented in tables D.5 and D.6 are largely unaffected by the disaggregation of capital. This suggests that this variable is not acting as a proxy for capital–skill complementarity, but rather reflects a separate mode of skill–technology interaction. The only exception being the finance industry. Finance's significant R&D intensity coefficient from table D.5 has been replaced by a significant coefficient on the computer variable, showing it to be a superior measure of the technology-skill relationship.

These results point to the desirability of disaggregating the capital stock when ascertaining the existence of SBTC. While, as expected, buildings and structures are of little importance for skill intensity, this is not true of other types of assets. The software variable, in particular, provides added support to the SBTC hypothesis.

Trade–augmented model

The addition of trade variables where available to the right hand side of the estimating equation has the effect of reducing the coefficient estimates for the wage bill share equations to insignificance, as shown in table D.8.[8] Only by dropping the R&D intensity variable is a significant coefficient obtained, in one division only and not on the trade variables. This is in contrast to the employment share regressions, in which coefficients for both import and export intensity are generally significant.

The signs of these coefficients are of interest for the three industries examined. In agriculture the negative significant coefficient on imports is at odds with predicted outcomes of the trade hypothesis. There is a positive and significant coefficient for mining which is consistent with the trade hypothesis. However, the low import penetration in the mining industry is unlikely to drive the observed upskilling in this industry. In manufacturing, the import intensity coefficient is positive and significant. This result does not support the broad thrust of the more detailed results

8 Services sectors are dropped due to lack of trade data. However, estimations are performed which included services and economywide measures of import and export intensity. The results are not significantly different from those reported here.

presented in table D.3. It is only consistent with its corresponding model, (ie CRS, employment shares), casting doubt on the validity of these results.

Table D.8 **Results[a] of SUR estimation with disaggregated capital and trade effects — divisions**

Standard error in brackets

	Dependent variable			
	Employment share[b]			*Wage bill share[c]*
Division	*Agri*	*Mining*	*Manuf*	*Agri[d]*
Explanatory variable[e]				
ln(B&S/Y)	0.021 (0.076)	0.086 (0.154)	-0.032 (0.058)	0.280 (0.276)
ln(M&E/Y)	-0.0342 (0.073)	-0.215 (0.192)	0.064 (0.055)	-0.255 (0.269)
ln(soft/Y)	-0.024* (0.004)	0.014 (0.010)	-0.001 (0.007)	-0.040# (0.022)
rdv	8.383* (3.787)	-2.540 (2.374)	-0.865 (0.692)	*(dropped)*
ln(I/Y)	-0.073* (0.014)	0.030* (0.013)	0.036# (0.019)	-0.037 (0.059)
ln(X/Y)	0.037# (0.020)	0.021 (0.028)	0.051* (0.021)	0.012 (0.091)

a Results are reported only for those industries for which the coefficient on at least one of the selected explanatory variables is significant. * = significant at the 5 per cent level. # = significant at the 10 per cent level. **b** Accommodation and Personal Services have been dropped due to missing observations. **c** Agriculture, Wholesale, Accommodation and Personal Services have been dropped due to missing observations. **d** Coefficient estimates in this column are for a model specification variant from which the R&D intensity variable has been dropped (as no estimates are significant in the model containing *rdv*). **e** All variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

On the other hand, export intensity is positive and significant in both agriculture and manufacturing, consistent with earlier findings (again see table D.3). The two other technology indicators, software intensity and R&D intensity provide conflicting results in the agriculture sector. Software is negative while R&D intensity is positive and significant. While the standard error of the rdv coefficient is quite large the coefficient remains in the positive region.

Overall, results for this model support earlier work by providing scant evidence of the trade hypothesis as the main factor driving the changing demand for high skilled workers in Australia. Rather, these results illustrate the economy’s reliance on high skilled labour to compete in overseas markets. This reliance is, on balance, more readily ascribed to SBTC than to the trade hypothesis.

High and low reform

The SUR technique is no longer possible after dividing the data into low and high reform periods due to the limited number observations in each period. Panel techniques have the benefit of substantially increasing the number of observations available so that a low/high scenario can be run. For this reason panel data techniques are applied. Although tests show a panel approach does not yield coefficient estimates as efficient as the SUR, it does provide unbiased estimates. The danger is in putting too much emphasis on the coefficient estimates themselves. Therefore, the panel results are reported but analysis is confined to changes between the periods.

Table D.9 **Results[a] of random effects estimation of the model with disaggregated capital and trade effects — divisions**

Standard error in brackets

Period	***Entire Period***	***Low reform***	***High reform***
		Dependent variable	
Explanatory variable[b]	*Employment Share*	*Employment share*	*Employment share*
ln(B&S/Y)	-0.227* (0.040)	-0.329* (0.042)	-0.221* (0.025)
ln(M&E/Y)	0.393* (0.025)	0.522* (0.057)	0.399* (0.063)
l(Soft/Y)	0.011 (0.009)	-0.042* (0.014)	0.024# (0.013)
rdv	0.720 (1.334)	-2.006 (6.432)	3.371# (1.771)
ln(I/Y)	-0.101* (0.012)	-0.036* (0.017)	-0.126* (0.017)
ln(X/Y)	-0.020 (0.035)	0.081# (0.043)	-0.044 (0.040)

a These results apply to three divisions only: agriculture, mining and manufacturing. * = significant at the 5 per cent level. # = significant at the 10 per cent level. **b** All variables as previously defined.

Source: Commission estimates based on data set detailed in appendix A.

Table D.9 reports the panel for the entire period, as well as the two subperiods to aid in interpreting the results. The entire period, covering 1978 to 1998, shows the two main technology parameters, R&D intensity and software intensity, are insignificant. However, the form of technology embodied capital, as captured in M&E intensity, is positive and significant. The individual period results point to this outcome being driven by the low reform years. After the implementation of microeconomic reform, R&D intensity is both significant and positive. The M&E coefficient continues to be positive and significant while the software variable is negative in the low reform period and then positive in the high reform period. This may indicate a change from high skill labour saving software implementation to high skilled labour enhancing in the high reform period.

On the trade variables, when estimating a single coefficient for import intensity, it turns out to be negative, the opposite of what the trade theory predicts. The export intensity variable is only significant in the low reform period. These results are inconsistent with the overall results presented above in the SUR analysis. It stands to reason that individual sector results are dominating and influencing these results.[9]

[9] Mining in the case of export intensity and agriculture for import intensity (see table D.8).

Broadly speaking, there appears to be significant technical complementarity between high skilled workers and R&D intensity as well as with capital (both software and M&E) in the later period. Given this outcome seems to be as a result of the economy's performance in the high reform period, it can be said the impact of microeconomic reform on the Australian economy was significant.

D.3 Conclusion

Overall evidence of SBTC using R&D intensity as a proxy for technology is more pervasive in the wage bill equations than for employment shares and in manufacturing than in divisions. There is evidence of SBTC through a positive and significant relationship for both dependent variables. The capital–skill complementarity evidence is consistent with the R&D results, that is, some among the division data, consistent in manufacturing. The trade hypothesis is not broadly supported in these results.

Examining the possible affects of microeconomic reform support the contention that reform has had an influence on the way the economy employs its resources. Evidence from both the manufacturing and division level data show that most of the results are driven by the post reform period. Also, that the significance of the technology proxies increases in this period. Thus, an argument can be made that through reform, businesses are able to re-examine their input mix and adjust accordingly.

Overall, the results provide strong support for SBTC in the levels form of the manufacturing data. It provides weaker support in the levels form of the division data. That is due to the fact that while the R&D intensity variable has the right sign, the capital intensity variable shows mixed results. The usual explanations for unsuspected results generally take three forms:

1. the model is mis-specified — the underlying assumptions determining the nature and form of the model need to be reassessed;
2. data problem — variables are incorrectly measured; and/or
3. the estimation technique is inappropriate for the dataset.

Given that there is strong evidence of SBTC in the manufacturing data and positive (if somewhat contradictory) evidence in the division data, (1) is generally rejected. Additional work indicates that option (3) is not the problem.[10] Finally, there is little

[10] Various specifications were undertaken to ensure the techniques applied were the most appropriate for the data collected. These included the Hildreth-Houck random coefficient method where all coefficients for each cross sectional unit are viewed as different realisations of

scope to control for problem (2) as a consumer, rather than producers of data. However, additional work currently undertaken will use two alternative approaches (and datasets) to see if these results reported here are sustained.

a variable with constant mean and variance; the Fixed-Slopes approach which is an extension of the fixed effects model allowing intercept values to differ across equations; and Generalised Least Squares approach which controls for various potential problems in the underlying dataset (such as autocorrelation). None of these methods were shown to be superior to those reported in this paper.

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