Estimating the monetary value of the stock of human capital for New Zealand

by

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Abstract

Human capital is increasingly believed to play an indispensable role in the growth process; however, adequately measuring its stock remains controversial. Because the estimated impact that human capital has on economic growth is sensitive to the measure of human capital, accurate and consistent measures are desirable. While many measures have been developed, most rely on some proxy of educational experience and are thus plagued with limitations. In this study, I adopt a lifetime earnings approach to estimate the monetary value of the human capital stock for New Zealand. I find that the country's working human capital increased by half between 1981 and 2001, mainly due to rising employment level. This stock was well over double that of physical capital. I also model human capital as a latent variable using a Partial Least Squares approach. Exploratory analyses on a number of countries show that age, gender and education combined can capture 65-97 percent of the explained variation in human capital.

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Chapter 1

Introduction

1.1 Background

According to Schultz (1961a), economists have long recognised that people are an important component of the wealth of nations. The origins of this notion can be found in Smith (1776), who included all acquired and useful abilities of a country's inhabitants as part of its capital. Even prior to that, Petty (1690), in an attempt to demonstrate the power of England, provided a monetary value of its human capital. As such, the concept of human capital is deeply and firmly rooted.

With the importance of knowledge in today's economy, human capital has increasingly attracted both academic and public interest. Theory suggests that it is human capital – the knowledge and skills embodied in people – rather than physical capital, that is vital to a country's economic prosperity. In practice, private and public investment in human capital, in the form of expenditure in education and training, amounts to over 10 percent

of national income in most OECD countries (Healy, 1998). Understanding human capital would, therefore, be important to politicians, economists and development strategists.

In the recent economic literature, interest in human capital revolves around economic growth. Traditionally, the focus on boosting growth was to give workers access to more physical resources, like land, factories and machines. But modern theories of economic growth, such as those of Romer (1986), Lucas (1988) and Jones and Manuelli (1990), emphasise human capital. According to these theories, human capital can foster growth through stimulating technological creation, invention and innovation, as well as facilitating the uptake and imitation of new technologies.

Numerous studies have sought to establish a relationship between human capital and economic growth. Although human capital has been found to boost growth in some cases,[1] positive results have failed to prevail in others.[2] The hypothesis that human capital plays a significant role in the growth process is not empirically validated.

This mixed evidence is believed to arise from measurement error in human capital, which comes in two forms. First, the proxies that have been used do not capture key elements of human capital. Second, data on the proxies are erroneous. Mismeasurement may account for the somewhat surprising finding that greater investment in human beings does not result in faster economic growth. This concern with measurement error has brought up a longstanding challenge for economists – how to measure human capital adequately?

[1]See, for example, Barro (1991), Benhabib and Spiegel (1994), Barro and Sala-i-Martin (1995), Gemmell (1996) and Sala-i-Martin (1997).

[2]Examples include Kyriacou (1991), Wolff (2000) and Bils and Klenow (2000).

Following the insights of Smith (1776), the creation of specialised labour is seen to require scarce inputs, typically education. This emphasis on education has led to a research agenda where human capital is proxied by school experience. In fact, human capital is often estimated on the basis of years of schooling or formal educational attainment levels, regardless of actual productive capacity (Miller, 1996). For example, New Zealand Treasury (2001) compares human capital in New Zealand to other OECD countries using average years of education, expected years of tertiary education, and participation rates in adult education and training. This educational approach is popular mainly because it uses measures that are relatively easy to quantify. But despite shedding some light on gross differences in economic growth between 'rich' and 'poor' countries, these crude proxies for knowledge are unable to satisfactorily explain the performance of more economically advanced economies like New Zealand. The proxy measures of human capital used by authors such as Nehru et al. (1995) and Barro and Lee (1993, 1996) have attracted considerable criticism.[3] Recently, some improvements have been made to the measurement of human capital.[4] However, by focusing on the education so far experienced, these measures still fail to capture the richness of knowledge embodied in humans.

As can be expected, the impact that human capital has on economic growth is sensitive to the measure of human capital. It is necessary that there be an accurate and consistent measure that will facilitate cross-sectional

[3]See De la Fuente and Doménech (2000), Temple (2000), Pritchett (2001), Krueger and Lindahl (2001) and Cohen and Soto (2001).

[4]See Oxley et al. (1999, 2000), De la Fuente and Doménech (2000), Cohen and Soto (2001), Barro and Lee (2001) and Wößmann (2003).

and temporal comparisons. Only when human capital is adequately and consistently measured can we understand how it affects the growth process and how governments or firms can influence its quantity or quality. The need for a reliable measure of human capital is reinforced by the fact that it is not yet standard practice for official statistical agencies to include human capital in their capital stock measures. This is a surprising omission seeing that the origins of monetary estimates of human capital predate the formal development of National Accounts statistics.

1.2 The relevance of measuring human capital to New Zealand

Forty years ago when Schultz (1961a) (re)introduced the concept of human capital, it was controversial if humans should be classified as 'capital.' Today, human capital has become a buzzword not only in academia but also in politics, business and the media.

Many entrepreneurs recognise the importance of human capital in today's business. For example, Chapman (2001) quotes Doug Marsh, president of Business New Zealand and a member of the New Zealand Institute of Management Inc. National Board, who pronounces that "economic growth is driven on achieving higher productivity. That means in part greater investment in human capital." But there is concern that a large amount of New Zealand human capital is wasted through mismanagement (Anderson, 1998). Indeed, the Watson Wyatt Human Capital Index survey of companies

in 12 Asia-Pacific countries reveals that New Zealand firms perform poorly on human capital management, and Watson Wyatt New Zealand managing director Paul Loof claims that "by improving human capital management, New Zealand firms can improve their bottom line" (Smith, 2002). It has been widely accepted that nowadays brains are replacing brawn as a strategic resource in New Zealand firms (Matheson, 2002; Tapsell, 1998), implying that traditional accounting methods no longer reflect the true value of a company on the balance sheet. Therefore, according to Tapsell (1998) and Bernacki (1998), measuring the value of human capital to a firm is a growing issue.

Human capital is even more frequently discussed in the policy context. Acemoglu (2001) suggests that rising income inequality in New Zealand is due chiefly to higher skill premia, which are in turn attributable to the uneven distribution of human capital. The author believes that income inequality can be reduced more effectively by policies that seek to close skill gaps between the top and the bottom of the income distribution than by those raising the average human capital in the economy without changing its distribution. Specifically, useful policies should aim at improving the quality of secondary schooling, rather than promoting college attendance.

Scobie et al. (2005), in an analysis of individuals' net worth, attempt to treat human capital as an asset. Indeed, capital acquired from farm and business loans and property mortgages are listed as assets on the balance sheet. Thus, human capital – a form of capital usually acquired through student loans – should also be considered an asset. Such treatment obviates recording negative net worth values for recent graduates, who have an outstanding student loan and hardly any financial and physical assets. Scobie

et al. find that human capital makes up a large component of total net worth, amounting up to four times the level of recorded financial and physical assets for a young adult.

Issues on human capital also receive attention from politicians. Former Prime Minister Jenny Shipley believes that New Zealand's future lies in developing human capital (Gawith, 1999). In a Budget speech, Finance Minister Michael Cullen unequivocally announces "the single most important prerequisite for lifting our productivity and economic growth rates is increasing human capital" (Cullen, 2001). A key goal which the current government has set out is to get New Zealand back to the top half of the OECD income rankings (Clark, 2002). This would entail an annual economic growth rate of at least 4 percent (New Zealand Treasury, 2004), and Cullen, again, has been repeatedly quoted to claim that improving human capital is the top priority to boost the country's economic performance (Laugesen, 2002; Venter, 2002; Weir, 2002). To the government, developing human capital means enabling easier access to tertiary education, improving staff ratios in early childhood education and expanding numeracy and literacy programmes. These policies are intended to lift the quality of the future workforce, while migrants are needed to fill the current skill gap (Clark, 2002).

The importance of human capital is also understood by official statistical agencies charged with measuring basic economic phenomena:

> Human capital is emerging as a key determinant of international competitiveness and its very long development period makes it necessary to understand the stock of the capital, the influences

> on it, and the way in which that capital and those influences alter... (Cook, 2000)

Nevertheless, the role of human capital is not unanimously acknowledged. Some commentators dismiss this term as 'political waffle.' Robertson (2001), for example, criticises the government for overstating the contribution of human capital to growth. Kerr (2002), executive director of the New Zealand Business Roundtable, believes that compared with other OECD countries New Zealand already has a high level of human capital, in terms of the level of innovation in manufacturing and services sectors and the uptake of technologies. Noting that the Soviet Union had excellent scientists and engineers whereas Switzerland has the lowest university attendance and graduation rates in the OECD, Kerr argues that the role of human capital in economic success should not be exaggerated at the expense of more critical issues.

How important is human capital to the New Zealand economy? Is the term human capital merely 'political waffle,' or is the role of human capital not well understood? Does New Zealand already have sufficient human capital, or does it still suffer from a shortage of human capital that needs to be filled by skilled migrants and more spending on education? The contradicting views to these questions can only be resolved when there is a reliable measure of how much human capital New Zealand actually has.

1.3 Research methods

The frequently used education-based method is only one of several approaches to the measurement of human capital. There are alternative models

which build upon Smith, Ricardo and modern labour economics more generally. In particular, these measures are based on the cost of production or the expected earnings of heterogeneous labour. These approaches have a rich and long intellectual pedigree and the advantages of easily permitting monetary values to be assigned to the stock and thus enabling comparisons with other types of capital. Most notable among these methods is the lifetime earnings approach introduced by Farr (1853). Following Farr, the basic idea is to value people's human capital as the total income that could be generated in the labour market over their lifetime. This framework has subsequently been innovated, most significantly by Jorgenson and Fraumeni (1989, 1992). Their major contribution was in simplifying the estimation process and in incorporating the potential value of current schooling besides that of existing schooling. Outside the US, this model has been applied to Sweden (Ahlroth et al., 1997) and Australia (Wei, 2003), both of which studies find the stock of human capital to greatly exceed that of physical capital.

In this thesis, I depart from Jorgenson and Fraumeni's assumptions that individuals make a decision over hours of work such that the marginal value of work equals that of leisure and that non-market human capital should be evaluated at the wage rate. These assumptions are contentious and have stimulated considerable debate.[5] For example, in the 'new' system of national accounts proposed by Jorgenson and Fraumeni (1989), the imputations for the 'services' of household durable goods and the value of household production and leisure time raise the total (real and imputed) income of households fivefold. As such, for the US economy the labour share appears as 93 percent

[5]See Eisner (1988), Ruggles (1991), Shaikh (1994) and Hersch and Stratton (1997).

and the property share 7 percent. Such results and implications, I believe, have undermined subsequent use of Jorgenson and Fraumeni's model. I argue here that full imputation of non-employment overstates a country's stock of human capital. The rates of participation and employment are important indicators of an economy's performance; assuming equal economic value between a full-time worker and a non-participant is not justifiable. For that reason, I exclude the human capital of those people who are out of employment as well as the contribution which employed individuals make outside paid work. My approach ignores the value of human capital stocks used in non-market production, but such a restricted focus is also common in studies measuring the returns to education. The working capital of employed individuals directly add value to economic production; hence, it is arguably a better measure of the country's productive capacity.

I use data from New Zealand Census of Population (1981-2001) to estimate human capital for each cohort classified by ethnicity, gender and education level. Various sensitivity analyses are also conducted. This is both of theoretical and practical importance, particularly for statistical agencies who may, as in the case of New Zealand and Australia, be actively engaged in pilot-studies of the regular collection of new, monetary measures of human capital. My measures of human capital are also contrasted with estimates of the physical capital stock. Furthermore, I decompose to explore what drives the recent changes in New Zealand's stock of human capital.

Arguably, possible determinants of human capital extend well beyond ethnicity, gender, education and age. This issue will be addressed by evidence from the micro level. I will employ a technique called Partial Least Squares

(Wold, 1975) which models human capital as a multidimensional latent variable that is affected by and reflected in many variables. This framework is capable of handling the multi-dimensionality of human capital instead of using observable indicators to proxy for the unobservable human capital. As such, it will be possible to examine how other variables are related to human capital and how significant their relationships are.

1.4 Structure of the thesis

The remainder of this thesis proceeds as follows. Chapter 2 surveys the literature on measures of human capital, where empirical evidence for New Zealand will be treated in greater detail. Chapter 3 estimates the stock of human capital for New Zealand using the Jorgenson and Fraumeni (1992) model. Modifications to the lifetime earnings method will follow in Chapter 4. A decomposition of changes in human capital is presented in Chapter 5. Chapter 6 introduces the Partial Least Squares approach for modelling human capital. Chapter 7 summarises and concludes.

Chapter 2

Literature review

2.1 Definitions of human capital

Schultz (1961a) classified skills and knowledge that people acquire as a form of human capital, and in so doing he sparked the revival of interest in the notion of human capital. A variety of definitions of human capital have since prevailed. For example, the Penguin Dictionary of Economics defines human capital as "the skills, capacities and abilities possessed by an individual which permit him to earn income." This concept has been extended to incorporate non-market activities, and a broader definition of human capital is "the knowledge, skills, competencies and attributes embodied in individuals that facilitate the creation of personal, social and economic well-being" (OECD, 2001, p18). Laroche et al. (1999) further extend the notion to include innate abilities. By definition, human capital is a complex concept; it has many dimensions and can be acquired in various ways (at home, at school, at work, and so on).

Clearly, human capital is *intangible*, the stock of which is not directly observable like that of physical capital. Therefore, estimates of the human capital stock must be constructed indirectly. Common approaches to human capital measurement include the cost-based approach, the income-based approach and the education-based approach.

2.2 The cost-based approach

A very common approach to the measurement of human capital is the cost-of-production method originated by Engel (1883), who estimated people's human capital based on rearing costs to their parents. Engel considered a person to be fully produced by the age of 26, so the cost of rearing a person would equal the summation of costs required to raise him from conception to the age of 25. Assuming that the cost of rearing a person aged $x < 26$, belonging the ith class at birth of c_{oi} and annual costs of $c_{oi} + k_i c_{oi}$ a year, Engel arrived at this formula:

$$c_{xi} = c_{0i} + xc_{0i} + \sum_{1}^{x} k_i c_{0i} = c_{0i} \left\{ 1 + x + \frac{k_i x(x+1)}{2} \right\} \tag{2.1}$$

However, as Dagum and Slottje (2000) point out, this model should not be taken as an estimation of human capital; it is merely a summation of historical costs and ignores the time value of money as well as the social costs that are invested in people. More recently, Engel's approach has been augmented based on the assumption that the depreciated value of the dollar amount spent on investment in human capital is equal to its stock value.

Kendrick (1976) and Eisner (1985, 1989) were among the seminal examples of systematically measuring the stock of human capital by a cost-based approach. Kendrick divided human capital investments into tangible and intangible. The tangible component consists of the costs required to produce the physical human being. Intangible investments, by contrast, aim at enhancing the quality or productivity of labour. They include expenditures on health and safety, mobility, education and training, plus the opportunity costs of students attending school.

This approach provides an estimate of the resources invested in the education and other human capital related sectors, which can be useful for cost-benefit analyses. It is also easy to apply, thanks to the ready availability of data on public and private spending.

However, as is well known with physical capital, there is no necessary relationship between investments and the quality of output: the value of capital is determined by the demand for it, not by the cost of production. This problem is more serious with human capital and thus renders cross-sectional and temporal comparisons unreliable. For example, an innately less able and less healthy child is more expensive to raise, so the cost-based approach will overestimate his human capital while underestimating well endowed children who, all else equal, should incur less rearing and educational expenses.

Secondly, the components entering into the production of human capital and their prices can not be easily identified. In particular, since how increases in each type of spending contribute to change in the human capital stock is not observable, it is difficult to distinguish between investment expenditures and consumption expenditures. For example, Kendrick classified

costs of raising children to the age of 14 as human capital investments, reasoning that these expenses, typically on necessities such as food and clothing, compete with other types of investment. This contradicts Bowman (1962) who argued against treating those costs as investments unless the men were slaves. Machlup (1984) concurred with this view, maintaining that basic expenditures should be considered consumption. There is a similar problem with determining the marginal contribution of each type of investment. Given the lack of empirical evidence, the researcher may have to allocate household spending quite arbitrarily between investment and consumption. Kendrick, for instance, assigned 50 percent of outlays for health and safety to human capital investment. Since most expenditures on people have both *consumption* effect (satisfying consumer preferences) and *investment* effect (enhancing productivity), cost-based measures are sensitive to assumptions about the type of spending and the share of various household and public expenditures that should be regarded as human capital investment. The difficulty in separating consumption effect from investment effect of 'expenditures on man' means that what should be considered human capital investment is controversial.[6]

Thirdly, the depreciation rate matters a great deal. Kendrick estimated depreciation in human capital by the (modified) double declining balance method. This is because physical capital depreciates faster in early years of life, so the double declining balance schedule is appropriate. To be consistent across different types of capital, Kendrick applied this method to depreciate

[6]See, for example, Schultz (1961a,b) and Shaffer (1961), who discussed the difficulties in distinguishing between consumption and investment expenditures in the formation of human capital.

human capital. By contrast, Eisner used the straight-line practice. Appreciation is often ignored, despite empirical evidence which showed that human capital appreciates at younger ages (Mincer, 1958, 1974). Graham and Webb (1979), who found evidence of human capital appreciation, criticised Kendrick for understating human capital by not allowing for appreciation while over-depreciating it.

There is ample empirical evidence on measures of human capital based on the cost approach, especially for the US. Schultz (1961a), for example, estimated that the stock of human capital of the US labour force increased by eight and a half times during 1900-1956 while the stock of reproducible capital grew only half as fast. Kendrick (1976) and Eisner (1985, 1989) provided more comprehensive estimates, opening the way to the construction of human capital time series using the perpetual inventory method.

Kendrick found that during 1929-1969, the stock of human capital often exceeded that of physical capital. In 1969, the US's non-human capital stock totalled $3,220 billion, whereas human capital was valued at $3,700 billion. In constant prices, the stock of human capital tripled over the period 1929-1969, at a growth rate of 6.3 percent a year, compared with an annual growth rate of 4.9 percent for non-human capital. Education and training accounted for 40-60 percent of the stock of human capital and this share increased consistently over time.[7]

Eisner (1985) departed from Kendrick's approach by allowing for the value of non-market household contribution to investment in child rearing. Investment in research and development also counted as human capital investment.

[7] All figures quoted in this sub-section are net stocks of capital.

While Kendrick divided human capital into tangibles and intangibles, Eisner classified it all as intangibles. His results showed that of the $23,746 billion worth of total capital in 1981, $10,676 billion was human capital. In real terms, human capital grew at 4.4 percent a year during 1945-1981 while capital in general increased at 3.9 percent a year. When put in the same price base, Kendrick's and Eisner's estimates are broadly similar, except that Kendrick's estimates of human capital often exceeded those of physical capital stocks, whereas the opposite was true of Eisner's.

2.3 The income-based approach

2.3.1 Early studies

The income-based approach to human capital measurement even predates the cost-of-production method. Petty (1690) was the first to use this framework. He calculated the human capital stock of England by capitalising to perpetuity the wage bill, defined as the difference between the estimated national income (£42 million) and property income (£16 million), at a 5 percent interest rate. This gave a result of £520 million, or £80 per capita. Petty's method was simplistic as it did not account for the heterogeneity of the population. Crude as it was, it raised the issue of estimating the money value of a country's labourers and gave an answer with a meaningful economic interpretation.

The first truly scientific model to estimating the value of a human being, according to Kiker (1966), was developed by Farr (1853). Farr calculated

the earning capacity as the present value of an individual's future earnings net of living expenses, adjusted for deaths in accordance with a life table. Using a discount rate of 5 percent, Farr estimated the average net human capital of an agricultural labourer to be £150, which is the difference between the average gross value of £349 and the average maintenance cost of £199. Farr's procedure laid a sound base for the income approach to human capital measurement. The underlying principle is to value people's human capital as the total income that could be generated in the labour market over their lifetime.

Dublin and Lotka (1930) followed Farr and devised a formula for calculating the value of an individual at birth, V_0, as:

$$V_0 = \sum_{x=0}^{\infty} \frac{S_{0,x}(W_x Y_x - C_x)}{(1+i)^x} \tag{2.2}$$

where i is the interest rate, $S_{0,x}$ is the probability of living to age x, W_x is the employment rate at age x, Y_x is the individual's annual earnings from age x to $x+1$, and C_x is the annual cost of living.

Equation (2.2) is a formal statement of Farr's method, except that Dublin and Lotka made allowance for unemployment. It can be extended to obtain the value of an individual at a given age a:

$$V_a = \sum_{x=a}^{\infty} \frac{S_{a,x}(W_x Y_x - C_x)}{(1+i)^{x-a}} \tag{2.3}$$

Similarly, the net cost of rearing a person up to age a is:

$$C_a = \sum_{x=0}^{a-1} \frac{S_{a,x}(C_x - W_x Y_x)}{(1+i)^{x-a}} \tag{2.4}$$

The right-hand side of equation (2.3) can be expanded:

$$\begin{aligned} V_a &= \sum_{x=0}^{\infty} \frac{S_{a,x}(W_x Y_x - C_x)}{(1+i)^{x-a}} - \sum_{x=0}^{a-1} \frac{S_{a,x}(W_x Y_x - C_x)}{(1+i)^{x-a}} \\ &= \sum_{x=0}^{\infty} \frac{S_{0,x}(W_x Y_x - C_x)(1+i)^a}{S_{0,a}(1+i)^x} + \sum_{x=0}^{a-1} \frac{S_{a,x}(C_x - W_x Y_x)}{(1+i)^{x-a}} \\ &= \frac{(1+i)^a}{S_{0,a}} \sum_{x=0}^{\infty} \frac{S_{0,x}(W_x Y_x - C_x)}{(1+i)^x} + \sum_{x=0}^{a-1} \frac{S_{a,x}(C_x - W_x Y_x)}{(1+i)^{x-a}} \end{aligned} \tag{2.5}$$

Combining (2.5) with (2.2) and (2.4), we have:

$$V_a = \frac{(1+i)^a}{S_{0,a}} V_0 + C_a \tag{2.6}$$

Equivalently,

$$C_a = V_a - \frac{(1+i)^a}{S_{0,a}} V_0 \tag{2.7}$$

This formula has a very intuitive interpretation: the cost of producing a person up to age a is equal to the difference between his current value and the present value, at age a, of his value at birth, adjusted for his survival probability to age a.

Other researchers also made important contributions. Wittstein (1867) combined Engel's cost-of-production approach with Farr's prospective method to evaluate the human capital of an individual at different ages.

However, he was criticised for unjustifiably assuming lifetime earnings and lifetime maintenance costs of an individual to be equal.

Nicholson (1891) derived the human capital stock by capitalising the wage bill, earnings of management, earnings of capitalists, earnings of salaried government officials, and the so-called "domesticated humanity" (the costs of producing wage earners). He claimed that the United Kingdom's stock of living capital was worth five times that of conventional capital. But by combining the prospective and retrospective methods like that, Nicholson was criticised for duplicating values. Specifically, the costs of producing wage earners, which were already counted in the "domesticated humanity," also appeared in the capitalised value of their earnings.

De Foville (1905) believed that the prospective method overstates human capital by not deducting consumption expenditures from earnings. He, therefore, estimated the stock of human capital for France by applying Petty's approach to earnings net of maintenance. Another French researcher, Barriol (1910) used Farr's approach to evaluate the "social value" of French male labourers. Assuming that lifetime income equals lifetime expenditures, Barriol computed this value by discounting their future expenditures, adjusted for deaths, at a 3 percent interest rate. This method differed from Farr's in that maintenance costs were not subtracted from earnings. But what made Barriol's work innovative was that he estimated the social value by age group.

In the US, experimental studies on this subject date back to the early twentieth century. Fisher (1908) used Farr's approach to measure human capital in order to assess the costs of preventable illness and death. Also based on a Farr-type method, Huebner (1914) found the US stock of human

capital to be worth 6-8 times the stock of conventional capital. Woods and Metzger (1927) used five methods, including those due to Petty and Farr, to tackle this issue. But these analyses, as pointed out by Kiker (1966), contained several erroneous assumptions.

Treadgold (2000) identified Wickens (1924) as a pioneer in human capital measurement. Wickens evaluated the stock of wealth in Australia's population by estimating the total discounted value of all future streams of services expected to be generated by the country's citizens. He divided the population into three groups: adults of working age (males aged 18-64 and females aged 18-59), juveniles (younger than 18), and the aged. The value of the annual services a person brings to the society was assumed to equal the weighted average gross earnings. These figures, corresponding to £133 and £65 for males and females respectively, were calculated from official weekly rates, with four weeks deducted from the working year to account for such factors as unemployment and unpaid holidays. Wickens further assumed that all surviving men would continue to earn £133 a year and women £65 until the retirement age. For the aged, old-age pensions were used in place of earnings. The "juveniles" were assumed to render no services before 18 and "adult services" subsequently. Combining these numbers with a life table and a discount rate, human wealth values would be obtainable for men and women at every age from 0 to 104.

Having human wealth values by age and gender, Wickens identified a median age for each of the three new groups (under 15, 15-64, and above 64) then multiplied the per capita wealth estimate of the median age by the population size of that group. He found that in 1915 Australia's human capital

totalled £6,211 million, or £1,246 per capita. This stock value was three times the stock of physical capital. However, Wickens's estimates were questionable, since he used such an unjustifiable shortcut to obtain the aggregate value and ignored the value of individuals in older age groups when deriving the value of people in younger age groups.

2.3.2 Critique

The income-based approach measures human capital by summing the discounted values of all future income streams that all individuals in the population expect to earn throughout their lifetime. This method is 'forward-looking' (prospective) because it focuses on expected returns to investment, as opposed to the 'backward-looking' (retrospective) method whose focus is on the historical costs of production.

The prospective approach seeks to evaluate a person's earning power. It values human capital at market prices, since the labour market more or less accounts for many factors, including ability, effort, productivity and education, as well as the institutional and technological structures of the economy (Dagum and Slottje, 2000). Also, there is no need to assume an arbitrary rate of depreciation, as depreciation is already implicitly captured. This method provides the most meaningful results if required data are available.

Indeed, accurate and timely life tables are readily available, and (un)-employment rates and earnings by age and education level can be obtained from relevant surveys. The choice of a discount rate involves some subjective judgment, but this should not be a problem. Above all, since the approach

based on income is forward-looking, a dynamic economy wanting to evaluate its future productive capacities would be more interested in this approach than the historical cost approach (Graham and Webb, 1979).

But this approach is not free from drawbacks. Most notably, the model rests crucially on the assumption that differences in wages truly reflect differences in productivity. In practice, wages may vary for other reasons. For example, trade unions may be able to command a premium wage for their members, or real wages may fall in economic downturns. Under such circumstances, income-based measures of human capital will be biased. These measures are also very sensitive to the discount rate and the retirement age.

Whether maintenance costs should be deducted is contentious. On the one hand, some authors argue that physical capital estimates are net of maintenance costs, thus human capital should also be net. De Foville (1905) and Eisner (1988), for example, criticised the income-based method for not deducting maintenance costs from gross earnings. Weisbrod (1961) attempted to account for maintenance, but he encountered many difficulties. What types of expenditures should be classified as maintenance, and how to account for economies of scale and 'public' goods when estimating per capita consumption for different members in the same household are problems that are not easily resolved. On the other hand, others maintain that consumption is an end, rather than a means, of investment and production, so gross earnings are more relevant to human capital derivation. It is argued that net productivity is a more adequate measure of a person's value to others; whereas gross productivity is a superior estimate of his total output to the society (Graham and Webb, 1979).

Another disadvantage of the income-based method is that data on earnings are not as widely available as data on investment. This is especially the case for developing countries, where the wage rate is often not observable. In the early studies reviewed above, the major problem lies in the lack of reliable data on earnings and the unjustified assumption about future earnings.

2.3.3 The revived interest in the income-based approach

Despite its merits, data constraints had prevented early researchers from utilising the income-based approach. Weisbrod (1961) was among the first to use cross-sectional micro data. He adopted Dublin and Lotka's (1930) formula:

$$V_a = \sum_{x=a}^{74} \frac{S_{a,x} W_x Y_x}{(1+i)^{x-a}} \tag{2.8}$$

where V_a is the present value of expected future earnings of a person at age a. The retirement age is 75, at which earnings are nil.

The use of cross-sectional data necessitates assuming that in n years, those currently aged x would earn an income equal to what people aged $x + n$ now earn. A similar logic applied to employment rates and survival probabilities. Weisbrod showed that in 1950, average human capital for US males aged 0-74 was \$17,000 at a discount rate of 10 percent and \$33,000 at 4 percent. Netted of maintenance costs, the corresponding figures would be \$13,000 and \$26,000 respectively. Apparently, even the lowest estimate of (male) human capital exceeded the stock of non-human assets of \$881 billion, consistent with the fact that labour income exceeded property income. Based

on these results, the author claimed that the society was paying too much attention to non-human capital, while it was human capital that deserved greater investment.

Weisbrod cautioned that such use of cross-sectional data overlooks changes in age-specific values over time. Since such changes tend to be positive, estimates of human capital under static age-specific conditions are likely to be biased downwards. Another source of underestimation was that median earnings were used, because mean earnings were not available.[8]

Houthakker (1959) and Miller (1965) argued that in a growing economy, everyone should benefit from an expected increase in their earnings on top of the gains in experience, seniority and other age-related factors. Also using data from the 1950 US Census, Miller demonstrated that by accounting for economic growth, estimates of lifetime income based on cohort analyses well exceeded those based on cross-sectional patterns.

Recognising the major limitation in Weisbrod (1961), Graham and Webb (1979) adjusted the framework to incorporate economic growth. They also departed from earlier studies by controlling for education. Equation (2.8) is then modified as follows:

$$V_a^i = \sum_{x=a}^{75} \frac{S_{a,x}^i W_x^i Y_x^i (1+g_k^i)^{x-a}}{(1+i_k^i)^{x-a}} \tag{2.9}$$

where the superscript i denotes a vector of personal characteristics and i_k^i and g_k^i are respectively the interest rate and growth rate in earnings that apply to type i individuals at the kth year of life. The underlying assumption

[8]As is widely known, for most earnings distributions, the mean is often greater than the median.

here is that a person aged x with characteristics i will base his expectation of earnings n years from now on what is earned by those who are currently $x + n$ years old and who possess the same basic characteristics.

Graham and Webb found that lifetime wealth rises with education at all ages and is concave in age at all education levels. Throughout the life cycle, human wealth initially rises, then approaches zero at retirement. The income-based framework implicitly allows for depreciation, so there is no need to assume an arbitrary depreciation rate. In aggregate, the stock of capital embodied in US males aged 14-75 in 1969 ranged from $2,910 billion at a 20 percent discount rate to $14,395 billion at a 2.5 percent rate. According to Kendrick's (1976) cost-based method, human capital in 1969 totalled $3,700 billion. Taken into account the difference in population bases, Kendrick's estimate was still comparatively lower than Graham and Webb's at the highest discount rate of 20 percent. They believed that Kendrick's estimates are biased downwards due to the incorrect assumption about depreciation.

2.3.4 The Jorgenson and Fraumeni method

Model

Graham and Webb's (1979) study was far more sophisticated than earlier ones, but it still contained methodological limitations and covered barely half of the US population. Jorgenson and Fraumeni (1989, 1992) augmented the method and proposed a new system of national accounts. They estimated the human capital of everyone in the US population classified by the two

sexes, 61 age groups, and 18 education groups (0-17+ years of schooling) for a total of 2,196 cohorts.

Jorgenson and Fraumeni's most significant contribution was in simplifying the procedure for discounting future income streams to the present value. Specifically, they noted that the present value of lifetime labour income for an individual of a given age is just his current annual labour income plus the present value of his lifetime income in the next period weighted by survival probabilities. By backwards recursion it is possible to calculate the present value of lifetime income at each age. For example, if people retire at 75, then for a 74-year-old person, the present value of lifetime labour income is simply his current labour income. The lifetime labour income of a 73-year-old individual is equal to his current labour income plus the present value of lifetime labour income of the 74-year-old, and so forth. Formally, the lifetime income V of an individual with sex s, age a, education e is given by:

$$V_{s,a,e} = Y_{s,a,e} + S_{s,a+1} V_{s,a+1,e}(1+g)/(1+i) \tag{2.10}$$

where Y is annual earnings and S_{a+1} is the probability that the person will survive another year. Jorgenson and Fraumeni identified five stages of the life cycle: no school and no work (ages 0-4), school but no work (5-13), school and work (14-34), work but no school (35-74), and no school or work (75 and older). By assumption, the lifetime income for the oldest group is zero, so is the annual income of those in the first two stages.

Also notably, Jorgenson and Fraumeni's method incorporates the potential value created by people who are currently attending school. Such inclu-

sion of enrolment affects the lifetime income of those in the second and third stages of the life cycle. For these people, lifetime income is:

$$\begin{aligned} V_{s,a,e} = Y_{s,a,e} + \{&E_{s,a,e} S_{s,a+1} V_{s,a+1,e+1} \\ &+ (1 - E_{s,a,e}) S_{s,a+1} V_{s,a+1,e}\}(1+g)/(1+i) \end{aligned} \tag{2.11}$$

where E denotes the school enrolment rate. Working backwards from the lifetime incomes of the most educated people, we can obtain lifetime income for individuals who are still at school.

Arguing that human capital is not restricted to market activities, Jorgenson and Fraumeni imputed the value of labour compensation for non-market activities (excluding schooling). They defined full labour income as the sum of market and non-market labour compensation after taxes. The formulae above apply similarly to both market income and non-market income. How income is divided between market and non-market depends on how much time is allocated to 'maintenance.' For example, Jorgenson and Fraumeni assumed 10 hours maintenance a day, so if a person works 40 hours a week, he would have $40 \times 52 = 2080$ hours for market activities and $(14 \times 7 - 40) \times 52 = 3016$ hours a year for non-market activities. Annual earnings, market and non-market, are derived from after-tax hourly labour compensation for each sex-education-age cohort.

Jorgenson and Fraumeni (1989) found that in 1982 prices the US stock of human capital almost doubled, from \$92 trillion in 1949 to \$171 trillion in 1984. In the later study (1992), the estimates were 20 percent higher, due to allowance being made for school enrolment. Population growth accounted for

most of the increase, as per capita human capital went up by only 15 percent. Women accounted for about 40 percent of the stock of human capital and this proportion remained fairly stable throughout the period. The share of human capital due to market activities was around 30 percent.

While cost-based studies found the human capital stock to be of similar value to the physical capital stock and while earlier income-based studies observed the former to be 3-5 times greater than the latter, Jorgenson and Fraumeni (1989) showed that human capital was worth 12-16 times more than physical capital. For the period 1948-1969, their (1992) estimates were from 17.5 to 18.8 times higher than Kendrick's (1976). According to Jorgenson and Fraumeni, this is because their estimates incorporates all sources of lifetime labour income, including investment in education, the value of rearing, and the lifetime incomes of individuals added to the population, prior to any investment in education or rearing. On the one hand, Kendrick was criticised for underestimating human capital by over-depreciating it. On the other hand, critics argue that Jorgenson and Fraumeni overestimated human capital through the treatment of non-market activities.

Even when biases are minimised, disparities in results from the two methods can hardly be avoided. As Graham and Webb (1979) pointed out, in a competitive equilibrium the value of a capital asset can be determined both by summing the costs of production and by discounting future returns. These two methods are equivalent in a world of complete certainty, perfect capital markets and no externalities. In reality, estimates from the two approaches can differ markedly since seldom do these conditions prevail.

Critique

The most controversial point of Jorgenson and Fraumeni's model is the assumption that human capital raises the productivity of time spent at leisure and at work equally. Rothschild (1992) refutes this argument. Their way of imputing non-market activities means that unemployment matters to the division of human capital between market and non-market activities but does not affect total human capital. As Conrad (1992) stresses, there would be no change in the human capital stock if the population is fully employed or only half employed, since non-work time will be fully imputed anyway. Besides, average earnings of workers are used to impute the value of non-market time for non-workers and this creates a sample selection bias problem. Aulin-Ahmavaara (2002) questions the full imputation of non-work time, seeing as at least some leisure time is necessary to prepare for work.

Dagum and Slottje (2000) also point out that Jorgenson and Fraumeni's model contains ability bias because it does not allow for variations in endowment among individuals of the same sex and education. Furthermore, the retirement age is set too high (Conrad, 1992); overvaluing older people's productivity results in overstating lifetime incomes for all other ages.

Applications to other countries

Wei (2003) applies Jorgenson and Fraumeni's framework to Australian data. Focusing on the working population, Wei only distinguishes two life-cycle stages: work and study (ages 25-34) and work only (35-65). The author identifies four education levels, based on qualifications, rather than 18 levels

based on years of formal schooling as in Jorgenson and Fraumeni. Like Graham and Webb (1979), Wei finds that education and human capital are positively related and that lifetime labour income initially rises then falls for all education levels. In 2001 prices, the stock of Australia's working-age human capital increased from $3.2 trillion in 1981 to $5.6 trillion in 2001, most of which growth was caused by rising number of educated individuals. Women accounted for approximately 40 percent of the total stock of human capital. Even for such a small population base, the stock of human capital always exceeded that of physical capital, and this ratio has been rising, from 2.8:1 in 1981 to 3.1:1 in 2001.

Ahlroth et al. (1997) show that Jorgenson and Fraumeni's model can also work with micro survey data. Since their data only have 6,000 individuals for 2,196 cohorts, most cohorts have few observations and some are even empty. Ahlroth et al. resolve this problem by using regression techniques to predict the values of hourly compensation, working hours, school hours, employment rates and school enrolment rates. They found that even the lowest estimates of Sweden's human capital stock (after-tax, excluding leisure income) were 6-10 times higher than the stock of physical capital.

2.3.5 The income-based index method

Also basing on income to estimate human capital, some authors seek to obtain an index value instead of a monetary measure. For example, Mulligan and Sala-i-Martin (1997) measure human capital as the total labour income per capita divided by the wage of the uneducated. The rationale for this

method is that labour income incorporates not only the workers' human capital but also the physical capital available to them, such that for a given level of human capital workers in regions with higher physical capital will tend to earn higher wages. Therefore, to obtain a 'pure' measure of human capital, the effect of physical capital should be netted out. Formally, the average human capital h of state i at time t is:

$$h_i(t) = \left\{ \int_0^\infty w_i(t,s)\eta_i(t,s)ds \right\} / w_i(t,0) \tag{2.12}$$

where $w_i(t,s)$ is the wage rate of a person with s years of schooling, $w_i(t,0)$ the wage rate of a zero-schooling worker, and $\eta_i(t,s)$ the fraction of people with s years of schooling.

This method assumes that uneducated workers always have the same human capital, although they do not necessarily earn the same income. According to Mulligan and Sala-i-Martin, if schooling has quality and relevance that vary across time and space, any amount of schooling will introduce inter-temporal and interregional differences in an individual's level of skills. Hence, the only sensible *numeraire* is the uneducated worker. The wage rate of such a worker is estimated by the exponential of the constant term from a Mincer wage regression.

Results indicated that the US stock of human capital shrank drastically during 1940-1950, then trended upwards until 1990. Interestingly, the human capital stock expanded by 52 percent between 1980 and 1990, whereas over the four preceding decades it grew by only 17 percent. Mulligan and Sala-i-Martin also find that although their measure of human capital correlates

well with average years of schooling, this correlation is not perfect. Their estimates of human capital increased much faster than schooling which, in the authors' view, was due to the improved quality and relevance of schooling.

Mulligan and Sala-i-Martin's measure clearly has some advantages. First, by netting out the effect of physical capital on labour income, this measure captures the variation in quality and relevance of schooling across time and space. Second, this method does not unrealistically impose equal amounts of skills on workers with equal amounts of schooling. Finally, it does not demand much data. However, this model relies heavily on the assumptions that zero-schooling workers are identical and that these workers are perfectly substitutable for the rest of the labour force. These assumptions, according to Wachtel (1997), are questionable. Moreover, this method neglects the contribution to human capital by factors other than formal schooling, such as informal schooling, on-the-job training and health.

Jeong (2002) departs from Mulligan and Sala-i-Martin in that he uses as the *numeraire* the industrial labourer, as classified by the International Labour Office. According to Jeong, industrial labourers, who primarily supply their physical effort with little skill, are more comparable across countries than any other types of workers. By not using schooling as a basis for comparing workers, Jeong's method avoids the problems that are inherent in education-based measures of human capital, namely the failure to account for schooling quality, for skills that are acquired outside formal schooling, and for variable rates of return to schooling across levels.

Not surprisingly, poorer countries use less human capital inputs in economic production and that the richest countries have from 2.2 to 2.8 times as

much human capital as the poorest countries. These figures, however, pale into insignificance in comparison with cross-country differences in years of schooling and in output levels.

In a study on Austria and Germany, Koman and Marin (1999) construct a measure of human capital stock by weighting workers of different schooling levels by their wage income. First, based on a perpetual inventory method, the number of individuals aged i whose highest level of schooling at time t is j is computed as:

$$H_{i,j,t} = H_{i-1,j,t-1}(1 - \delta_{i,t}) + H^{+}_{i,j,t} - H^{-}_{i,j,t} \tag{2.13}$$

where $H^{+}_{i,j,t}$ is the number of people aged i who completed education level j at time t, $H^{-}_{i,j,t}$ is the number of individuals aged i whose highest level of education was j in time $t-1$ and who completed a higher schooling level in time t, and $\delta_{i,t}$ is the probability that those aged $i-1$ in time $t-1$ died before reaching age i. After converting each schooling level j into years of schooling, the authors use a Cobb-Douglas aggregator to relate workers with different educational attainment to human capital h:

$$h = \ln\left(\frac{H}{L}\right) = \sum_{s} \omega_s \ln(\rho(s)) \tag{2.14}$$

where $\rho(s) = \frac{L(s)}{L}$ is the share of working-age individuals with s years of schooling; $\omega_s = \frac{e^{\gamma s}L(s)}{\sum_s e^{\gamma s}L(s)}$, the share of the wage income of workers with s years of schooling in the total wage bill of the economy, is the efficiency parameter of those workers; and γ's, the slope coefficients that capture the effect of schooling on earnings, are obtained from a Mincer wage regression.

Koman and Marin's framework measures workers' productivity by their wage income. Similar to Mulligan and Sala-i-Martin's (1997) approach, Koman and Marin's efficiency parameter ω_s nets out the effect of physical capital on wages (and hence on human capital). The use of a non-linear aggregator also avoids assuming that different education levels are perfectly substitutable. A limitation remains, however, as the model assumes that one year of schooling yields the same amount of skills over time. Koman and Marin find that their measure of human capital grew faster than average years of schooling and that the time-series evidence is not consistent with a human capital augmented Solow model. Interestingly, with the inclusion of human capital, factor accumulation is less able to explain cross-country growth performance of Austria and Germany.

Laroche and Mérette (2000) adopt Koman and Marin's model but additionally account for work experience. Canada's human capital, as defined by average years of schooling, increased by 15 percent during 1976-1996. The growth is 33 percent higher when human capital is measured using Koman and Marin's income-based approach, as higher education levels command rising premia. When experience is considered, average human capital grew by up to 45 percent. While the two human capital measures (including and excluding experience) were virtually the same from 1976 to 1981, they diverged afterwards. According to Laroche and Mérette, this is because before 1981 schooling contributed more to human capital than work experience whereas after that the reverse was true. This pattern is reinforced by the fact that the Canadian population has grown older and as this greying trend is expected to persist, the gap between the two measures is likely to widen.

2.3.6 Other income-based methods

Also income-based, but Macklem's (1997) measure has a macro focus. He calculates human capital as the expected present value of aggregate labour income net of government expenditures, based on an estimated bivariate vector autoregressive model. This method requires little data. According to the author, it also permits greater recognition of the joint statistical properties of innovations in income and interest rates. These advantages are, however, counteracted by the less disaggregated information.

Macklem finds that in per capita terms, human wealth in Canada rose steeply during 1963-1973, then fell until the mid-1980s, but has picked up since. First, this was because the real interest rate was very low in the mid-1970s and high in the 1980s – a higher interest rate reduces the cumulative growth factor and thus human wealth. Second, net income in the early 1980s was lowered by the increases in government expenditures and the drop in labour income due to the recession in the same period. Third, in the second half of the 1980s real interest rates were falling while net income was growing strongly, reversing the earlier downward trend in human wealth. Since this human wealth (capital) measure is income-based, it has a pro-cyclical pattern with economic downturns. However, Dagum and Slottje (2000) criticise Macklem's estimation for containing large, unacceptable and unsubstantiated fluctuations, in a period when Canada experienced steady economic growth. In the critics' view, this paradox is caused by the limitations in the exogenous variables specified in the bivariate autoregressive model.[9]

[9] A summary of studies that use cost-based, income-based and integrated approaches to human capital measurement is provided in Appendix Table 1.

2.4 The education-based approach

Unlike the 'conventional' approaches which measure capital by cost or by yield, the educational approach estimates human capital based on such educational output indicators as literacy rates, enrolment rates, dropout rates, repetition rates, average years of schooling and test scores. This method builds on the grounds that these indicators are closely related to investment in education and that (investment in) education is a key element in human capital formation. Educational indicators are, therefore, proxies for, not direct measures of, human capital. Of course, human capital encompasses more dimensions, but education is arguably the most important component. Indeed, for individuals, education can enhance well-being not only by opening up broader economic opportunities but also through non-market benefits such as improvements in health, nutrition, fertility, upbringing of children, opportunity for self-fulfilment, enjoyment and development of individual capabilities (Haveman and Wolfe, 1984). For the society, education plays a central role in economic, institutional, social and technological development.

2.4.1 Adult literacy rates

Typically defined as the proportion of the population aged 15 and older who are able to "read and write a simple statement on his or her everyday life" (UNESCO, 1993, p24),[10] adult literacy rates convey meaningful information about a country's general educational status. This indicator has been used

[10]This is a rather 'narrow' definition of literacy; various definitions of literacy are discussed in Chowdhury (1995).

in early empirical studies that control for human capital in growth equations, including Romer (1989) and Azariadis and Drazen (1990).

As can be expected, the so-defined human capital variable has shown limited explanatory power in cross-country growth regressions. One, perhaps minor, reason lies in the fact that literacy is not objectively and consistently defined across countries and thus creates biases in international comparisons. A more important reason is, despite reflecting a fundamental component of human capital, adult literacy rates miss out most of the elements that extend beyond that elementary level, such as numeracy, logical and analytical reasoning and scientific and technological knowledge. Using adult literacy as a proxy for human capital thus ignores the contribution of more advanced skills and knowledge to productivity. As Judson (2002) assesses, literacy rates might be a good proxy for human capital in countries where the populace has little education, but not for those with universal primary education.

2.4.2 School enrolment rates

School enrolment rates measure the number of students enrolled at a given level relative to the population of the age group who, according to national regulation or custom, should be attending school at that level. Net and gross enrolment rates are distinguished by the numerator of the ratio. Specifically, gross enrolment rates use the total number of students enrolled at the given level, whereas net enrolment rates exclude those students who do not belong to the designated age group.

Studies that use school enrolment rates as proxies for human capital in augmented growth models include Barro (1991), Mankiw et al. (1992), Levine and Renelt (1992) and Gemmell (1996). Such use is justified by the notion that the enrolled population represents the flow that adds to the existing stock of education to establish subsequent stocks. That is, enrolment rates measure the current investment in human capital that will be reflected in the stock of human capital sometime in the future.

However, enrolment rates prove poor proxies for the present stock of human capital. First, being measures of flows, enrolment rates only capture part of the continuous accumulation of the stock of human capital. Second, there is a long lag between investment in education and additions to the human capital stock; hence, current enrolment rates are indicators of the schooling level of the future, rather than current, labour force. Third, the education of current students may not be fully added to the (future) productive human capital stock because graduates may not partake in the labour force and because investment may partially be wasted through grade repetition and dropouts. Fourth, change in the stock of human capital is the difference between the human capital of those who enter and those who exit the labour force, but school enrolment rates take no account of the latter. Therefore, school enrolment rates do not even accurately reflect future flows of the human capital stock, let alone current flows or the current stock itself.

Moreover, data on school enrolment in developing countries often lack reliability. According to Barro and Lee (1993), UNESCO enrolment data primarily come from annual surveys of educational institutions in each country and reporters often overstate enrolment figures for the sake of their institu-

tions. Besides, there could be a reverse causality between enrolment rates and productivity growth – high enrolment may result from high productivity growth, rather than vice versa (Wolff, 2000).

In view of the pros and cons, school enrolment rates can be at best satisfactory proxies for human capital in some countries but not in others. For example, secondary enrolment rates will only be good proxies for human capital accumulation in countries where secondary education is expanding the most rapidly (Judson, 2002). Indeed, this author observes positive correlations between growth and human capital accumulation at the primary level for poor countries, at the secondary level for middle-income countries, and at the higher levels for rich countries, but no relationship between growth and human capital is found for the pooled sample.

2.4.3 Average years of schooling

Average years of schooling has several advantages over literacy rates and school enrolment ratios. First, it is a valid stock measure. Second, it quantifies the accumulated educational investment in the current labour force. Wachtel (1997) shows that under some reasonable assumptions, the number of schooling years is equivalent to cost-based measures of human capital.

Since primary data on years of schooling are not normally available at the country level, researchers have to construct their own data. Typically, UNESCO data on enrolment and attainment levels are used in the estimation. The studies that have attempted to develop data series on years of schooling can be divided into three groups based on the method they em-

ploy: the census/survey-based estimation method, the projection method, and the perpetual inventory method.[11]

The census/survey-based estimation method

Psacharopoulos and Arriagada (1986, 1992) were the first to compile data on average years of schooling for countries:

$$\overline{S} = \sum L_i D_i \tag{2.15}$$

where L_i is the proportion of labour-force participants with the ith level of schooling and D_i the duration in years of the ith level. Data on L_i were available directly from national censuses and surveys for 66 countries. For another 33 countries, the corresponding statistics had to be derived based on the educational composition of the population classified by sex and age.

Average educational attainment ranged from a low of 0.5 for Mali (1976) to a high of 12.6 for the US (1981). In addition to Mali, labour-force participants in Nigeria (1967) and Maldives (1977) had also attained on average less than one year of schooling. Mali and Nigeria, indeed, belonged to the region (West Africa) where workers were the least educated, having only 1.8 years of schooling on average. By contrast, workers in Eastern European countries and developed countries had over 10 years of schooling each. With 11.7 years per person in the labour force, New Zealand (1981) ranked third, next to the US (12.6 years) and East Germany (11.9).

[11] This classification is similar to that of Wößmann (2003).

For those who did not complete each schooling level, it was not known how many years they had finished. The authors thus assumed that these individuals have attended half of the duration of the corresponding level. This arbitrary assumption is a potential source of measurement error, since dropout rates vary considerably across countries. Moreover, of the 99 countries covered, only for 34 countries were more than one observation available. Cross-country comparisons are further hampered by the fact that the year of observation varies from country to country, extending from 1960 to 1983 and that labour force is defined differently across countries.

The projection method

Kyriacou (1991) sought to overcome limitations in Psacharopoulos and Arriagada's (1986) study by using a projection method. He regressed the years of schooling data available from Psacharopoulos and Arriagada (1986) for 42 countries in the mid-1970s (from 1974 to 1977) on lagged gross enrolment ratios obtained from UNESCO Statistical Yearbook:

$$S_{1975} = \beta_1 + \beta_2 Prim_{1960} + \beta_3 Sec_{1970} + \beta_4 High_{1970} \tag{2.16}$$

where $Prim$, Sec and $High$ denote enrolment ratios for primary, secondary and higher education. Observing a high R^2 coefficient (0.82), Kyriacou used the estimated coefficients to predict average years of schooling for other years (1965, 1970, 1980, 1985) and other countries. In that way, five observations were obtainable for most of the 113 countries covered. This data set shows even larger dispersion in schooling attainment than in Psacharopoulos and

Arriagada's data, ranging from 0.15 for Chad in the mid-1960s to 12.1 for the US in the mid 1980s. For New Zealand, the estimate increased from 8.0 to 9.3, while the country's rank fell from 5 to 12 over the period studied.

The richness in Kyriacou's data comes at the expense of substantial measurement error. His model assumed that the relationship between lagged enrolment ratios and years of schooling was stable across time and countries when in practice it never was (UNESCO, 1978). Similarities in the length of each schooling level, dropout rates and repetition rates were also implied. These strong assumptions explain why the estimates correlate well with the original data for the mid-1970s but differ massively for other periods.

The perpetual inventory method

Lau et al. (1991) used a perpetual inventory method, which computes the stock of education S at year T by summing the enrolments E at all grade levels g for all age cohorts:

$$S_T = \sum_{T-a_{\min}+6}^{T-a_{\max}+6} \sum_{g=1}^{g_{\max}} E_{g,t}\theta_{g,t} \tag{2.17}$$

where $\theta_{g,t}$ is the probability that an enrolee in grade g at time t will survive to the year $T, a_{\min} = 15$ and $a_{\max} = 64$ are respectively the youngest and oldest working ages. Setting the age of school entry at six, we have $T - 64 + 6$ as the year when the oldest cohort entered school, whereas the youngest cohort started school in year $T - 15 + 6$.

This method is very data demanding. Estimating the total years of schooling for the population aged 15-64 during 1965-1985 requires data on

school enrolment and mortality probabilities that go as far back as 1907. Substantial measurement error is likely, because pre-1950 and post-1980 data on enrolment were not available and thus needed to be extrapolated, and data gaps needed to be filled by interpolation. The heavy reliance on 'fabricated' statistics and the lack of benchmarking against census data is probably the major reason why Lau et al.'s estimates are poorly correlated with those from Psacharopoulos and Arriagada (1986). More biases could also result from ignoring dropouts, grade repetition and migration.

Nehru et al. (1995) modified Lau et al.'s method to correct for dropouts and repetition:

$$S_T = \sum_{T-a_{\max}+6}^{T-a_{\min}+6} \sum_{g=1}^{g_{\max}} E_{g,t}(1 - r_{g,t} - d_{g,t})\theta_{g,t} \tag{2.18}$$

where $r_{g,t}$ and $d_{g,t}$ are repetition rates and dropout rates, which are assumed to be constant over time and across grade levels, due to data constraints. Another merit of this study is that it collected enrolment data that go as far back as 1930 for most countries and in some cases to 1902, thereby reducing the errors caused by backwards extrapolation.

Nehru et al. found that workers in sub-Saharan Africa were the least educated, having acquired only 2.5 years of schooling per person by 1987. Along with East Asia, sub-Saharan Africa experienced the fastest growth in schooling, averaging 4.2 percent per annum during 1960-1987. By contrast, the corresponding growth was only 0.3 percent for industrial countries. This is because workers in these countries had received as many as 10 years of

schooling per person. New Zealand performed somewhat below the industrial countries' average, with only 8.9 years per worker in 1987.

Nehru et al. chose to ignore census data on attainment levels because most countries in their sample have more than one census observation and they could not determine what data point to benchmark their estimates against. Moreover, they argued that census-based estimates are not necessarily superior to estimates based on a perpetual inventory method. As a result, their study has been criticised by De la Fuente and Doménech (2000), who claim that disregarding the only direct information available on the variable of interest is hardly justifiable.

The Barro and Lee studies

Barro and Lee (1993) combined the three estimation methods. In fact, they applied essentially the same approach as Psacharopoulos and Arriagada's (1986, 1992); the departure in their study is on how missing data are filled.

Since census and survey data on attainment levels are available for only 40 percent of the observations, data gaps needed to be closed using other sources. Observing a high correlation (0.95) between adult illiteracy rates and the share of uneducated individuals for 158 observations, Barro and Lee used the former to fill missing data on no schooling. This exercise provided another 16 percent of the observations. Next, to impute missing data at the other broad categories (first level total, second level total and higher) the authors applied a perpetual inventory method which involves using census/survey data on attainment rates as benchmarks and estimating changes from these benchmarks on the basis of school enrolment ratios and the age structure of

the population. Estimates for the sub-categories (incomplete/complete) of each level (primary, secondary and higher) were next obtained by regressing the observed completion ratios on five- and ten-year lagged values or lead values and on regional dummies. Incompletion ratios were eventually determined using various ways. With sufficient information on attainment rates, average years of schooling can be computed using a similar formula to (2.15).

Ahuja and Filmer (1995) built on Barro and Lee's (1993) data but used a different method to impute missing enrolment data and corrected enrolment rates for repetition and dropouts. For 1985, their estimates of average years of schooling show high correlation (from 0.88 to 0.95) with those from Kyriacou (1991), Barro and Lee (1993) and Nehru et al. (1995). Their projections suggest that the strongest growth in human capital will be seen in the Middle East and North Africa, whereas sub-Saharan Africa, already the least educated region, will experience the lowest growth.

Barro and Lee (1996) also extended to ages 15-24 and used net enrolment ratios to avoid overstating enrolments. In the most recent revision (2001), gross enrolment ratios adjusted for repetition are used, so that children who enter school earlier or later are not incorrectly missed out. Allowance is also made for variations in the duration of schooling levels over time.

The Barro and Lee studies show that South Asia did not only have the lowest average years of schooling but also the highest gender inequality in education. In 1960, females in this region received 28 percent as much schooling as males, rising to 48 percent in 1985. By contrast, in OECD countries the gender ratio has stabilised around 94 percent. Interestingly, while New Zealand never got to the top 10 in Kyriacou's and Nehru et al.'s data sets, it

frequently tops Barro and Lee's lists. Besides, Barro and Lee's (1993) estimates for some countries (Portugal, Spain and Turkey) appear substantially lower than the corresponding estimates from Kyriacou which, according to Wolff (2000), is too large to be attributable to the difference in population bases alone. However, Wolff observes that Barro and Lee's data show greater internal consistency over time than Kyriacou's. This view is shared by De la Fuente and Doménech (2000), who assess that Barro and Lee's procedure should be theoretically superior to Kyriacou's because it utilises more information and avoids making strong implicit assumptions.

But De la Fuente and Doménech point out that the widely used Barro and Lee data contain a lot of noise, leading to unjustifiable inconsistencies in country rankings across data sets as well as implausible jumps and breaks in the time-series patterns. To make their case, the critics draw on attainment data from previously unexploited sources to revise Barro and Lee's (1996) data for OECD countries. They use interpolation and extrapolation, rather than the perpetual inventory method, to impute missing observations. These authors rely on subjective judgment to select the most 'plausible' figure in the presence of multiple observations or sharp breaks. According to their estimates, in 1990 New Zealanders aged 25 and above had on average 12.1 years of schooling, compared with 11.2 as in Barro and Lee (1996), yet the country's ranking in the OECD went from third place down to sixth place.

Most interestingly, De la Fuente and Doménech's estimates outperform those developed by Barro and Lee (1996) or Nehru et al. (1995) in several growth specifications. Although De la Fuente and Doménech's method involves considerable guesswork and lacks scientific underpinning, their results

lend support to the argument that poor data quality is a principal cause behind the 'growth puzzle' – the lack of relationship between economic growth and human capital formation – in the recent literature.

Also critical of Barro and Lee's estimates, Cohen and Soto (2001) seek to minimise potential error by obtaining as much observable data as possible. Missing data are imputed based on the assumption that the school attainment of the population aged T in one census is equal to the school attainment of the population aged $T-n$ in the census conducted n years earlier or, when this information is not available, the attainment of the population aged $T+m$ in the census conducted m years later. Only in the absence of relevant census information do Cohen and Soto resort to enrolment data and the perpetual inventory method.

Cohen and Soto's estimates correlate well (about 90%) with Barro and Lee's (2001), but the correlation drops to below 10 percent in first differences. The authors maintain that this disagreement is caused by Barro and Lee's estimates being plagued with measurement error, which is most visible from the several 'implausible' figures. Cohen and Soto also believe that while Barro and Lee's estimates are biased downwards, De la Fuente and Doménech's (2000) are biased in the opposite direction, even though very high correlation (94%) is observed between the latter and their results.

Summary

The sound theoretical grounds and reasonable availability of data are major reasons why years of schooling has been widely used in human capital studies, at both micro and macro levels. Years of schooling has become the most

common proxy for human capital in growth models.[12] However, it does not seem to improve the explanatory power of cross-country growth regressions. Such a disappointing outcome is often attributable to many imperfections inherent in this indicator.

First, years of schooling fails to account for the fact that costs and returns of education vary hugely from level to level. This measure incorrectly assumes that one year of schooling always raises human capital by an equal amount. For example, a worker with 10 years of schooling is assumed to have 10 times as much human capital as a worker with one year of schooling. This assumption is at odds with the empirical literature which has typically documented diminishing returns to education (Psacharopoulos, 1994).

Second, no allowance is made for differences in quality of education across time and space. Behrman and Birdsall (1983), based on some Brazilian evidence, found that neglecting quality of schooling biased returns to schooling. Since the quality of schooling varies more considerably across countries than within one country, overlooking quality is likely to create more severe biases.

Third, this measure unrealistically assumes that workers of different education categories are perfect substitutes for each other, as long as their years of schooling are equal. As Judson (2002) puts it, using years of schooling as a human capital stock measure is analogous to estimating physical stocks by counting the number of buildings, rather than valuing different kinds of buildings differently.

[12]Examples include Barro (1997, 1999); Barro and Sala-i-Martin (1995); Benhabib and Spiegel (1994); Islam (1995); Krueger and Lindahl (2001); Temple (1999); Wolff (2000).

Fourth, it is debatable whether or not schooling raises productivity. Starting from Arrow (1973), there has been evidence that schooling does more to 'signal' abilities to employers than to truly enhance skills. If this was the case, years of schooling may increase even when the true (but unobservable) human capital remains the same. In reality, the effect of schooling may be less extreme, but to the extent that schooling has a 'signalling' effect, years of schooling will be a biased measure of human capital.

Moreover, years of schooling completely ignores all human capital elements other than formal schooling, including health, on-the-job training, informal schooling and work experience. A clear example is that this measure treats uneducated individuals as having no human capital, even though in practice they are economically valuable as long as they work.

Data quality introduces another source of measurement error. As reviewed earlier, the methods that have been used to estimate schooling years are more or less flawed. Many authors, including De la Fuente and Doménech (2000), Krueger and Lindahl (2001) and Cohen and Soto (2001), argue that it is the lack of good data, rather than the characteristics of the variable itself, that has rendered years of schooling a poor proxy for human capital. This is quite clear from the discrepancies in New Zealand's rankings across data sets, ranging from top positions in Barro and Lee (1993, 1996, 2001) to 21st place in Nehru et al. (1995).

According to Krueger and Lindahl (2001), until recently, the macro literature had not paid adequate attention to potential problems caused by measurement error in education. These authors show that country-level schooling data are no more reliable than micro data. For example, the correlation be-

tween schooling data from Barro and Lee (1993) and Kyriacou's (1991) in 1985 is 0.86, dropping to 0.34 for changes between 1965 and 1985. Additional estimates of the reliability of country-level data further confirm their belief that measurement error in education severely distorts results from growth regressions that control for human capital (Krueger and Lindahl, 2001).[13]

2.4.4 Quality of schooling

According to Hanushek and Kimko (2000), quality issues have been neglected because it is taken for granted that variations in the quality of human capital are of much less importance than variations in its quantity. Such an omission has proved a mistake.

Recognising the limitations that contaminate measures of quantity of schooling, Barro and Lee (1996) and Lee and Barro (2001) allow for the quality dimension. They consider such input indicators as public educational spending per student, pupil-teacher ratios, salaries of teachers and length of the school year, and such outcome indicators as repetition and dropout rates. In fact, these measures are more or less a version of the cost-based approach to human capital evaluation.

As summarised in Appendix Table 4, not only does New Zealand lag behind the OECD average but it also ranks very low by international standards, especially on pupil-teacher ratios at the secondary level, ratios of government educational spending per pupil to GDP per capita and ratios of primary school teachers' salaries to GDP per capita. However, the country

[13] Appendix Tables 2-3 contain a summary of studies that measure the stock of human capital based on average years of schooling.

fares much better on the outcome measures (repetition rates and dropout rates). While New Zealand's rankings on the input indicators have improved over time, its rankings on the outcome side have worsened.

Barro and Lee (2001) introduce another 'quality' measure: test scores. In theory, test scores are good human capital indicators because they measure educational outcome, cognitive skills, and they ensure international comparability. Until the early 1990s, New Zealand students scored well in mathematics, science and reading. Yet their performance is more disappointing in the most recent test (the Third International Mathematics and Science Study, TIMSS, 1994-1995), where New Zealand ranked 23rd out of the 37 participating countries (see Appendix Table 5).

Unlike tests for students, the International Adult Literacy Test (IALS) directly measures the human capital of labour-force participants, and unlike other schooling indicators, this test captures the knowledge that is gained outside formal education. Therefore, IALS test scores have attracted considerable interest, as well as criticism, in human capital measurement. New Zealand performs poorly in this test, ranking from seventh on prose literacy to 13th on quantitative literacy out of a sample of 20 countries. These results put New Zealand on par with Australia and the US but well below the top performers (Sweden, Norway, Finland and Denmark). Overall, there is huge variation in literacy scores across OECD countries, despite the similarity in average years of schooling in their labour force. Barro and Lee (2001) also notice a large discrepancy in achievement between students and adults. For example, the correlation between the TIMSS mathematics score for seventh

grade students and the IALS quantitative literacy score for adults, in the common sample of 17 countries, is only 0.32.

The existence of so many 'quality' measures, most of which are poorly correlated with each other and with quantity measures of schooling, seems to create confusion rather than to resolve the human capital measurement puzzle. Those education-based measures of human capital, the most widely used measures of this variable, produce results that are often at odds with each other. The case of New Zealand provides a telling example: ranking for this country varies wildly not only across indicators, from first to 117th, but also across different data sets of the same indicator, from first to 20th (see Appendix Tables 3-6).

To settle this problem, Hanushek and Kimko (2000) develop a measure that incorporates all available information on international mathematics and science test scores. Data are available for 26 performance series for different ages, sub-test scores, and various years from 1965 to 1991. For their first measure (QL1), data on each of the series are transformed to having a world mean of 50. The second measure (QL2) adjusts all scores according to the US international performance, modified for the national temporal pattern of scores provided by the National Assessment of Educational Progress (NAEP). These national tests serve as an absolute benchmark to which the US scores on international tests can be keyed, whereby the mean of each international test series is allowed to drift in reference to US NAEP score drift and to the mean US performance on each international comparison. Measures of schooling quality for each country are then constructed by averaging

all available transformed test scores, weighted by the normalised inverse of the country-specific standard error for each test.

Hanushek and Kimko's measure has the advantage of combining various indicators of quality in one index, but it can be misleading because test scores do not just reflect schooling quality – they may also pick up unobserved variables, such as innate abilities. Besides, a measure of schooling quality is not necessarily a good measure of labour-force quality, as past and current students may be quite different from current workers. Moreover, because data on internationally comparable test scores are limited, Hanushek and Kimko have to impute missing values and in that way can not escape from the second type of measurement error, namely low data quality.

Wößmann (2003) makes further improvements by incorporating Hanushek and Kimko's quality measure into stock measures. First, the author expresses Hanushek and Kimko's estimate for each country as a ratio to the estimate for the US. This relative measure can be used as quality weights for a year of schooling in a country, with the weight for the US being unity. World average rates of return to education are finally integrated to arrive at a quality-adjusted measure of human capital stock:

$$h_i^Q = e^{\sum_a r_a Q_i s_{ai}} \tag{2.19}$$

where r_a denotes the world average rate of return to education at level a, Q_i refers to Hanushek and Kimko's educational quality index for country i relative to the US value, and s_{ai} is average years of schooling at level a in country i.

Employing data from Barro and Lee (2001) for average years of schooling, from Psacharopoulos (1994) for average rates of return to education, and from Hanushek and Kimko for a of schooling quality, Wößmann shows that New Zealand is the richest country in the world in terms of human capital, having 150% more human capital per person than the US (see Appendix Table 6).

Wößmann's measure allows human capital to rise continually, just like physical capital, instead of being bound by a limit like other quantity measures of human capital. Furthermore, this measure captures quantity as well as some aspects of schooling quality in one single number. However, this method is very data demanding, and to the extent that the estimates in Barro and Lee (2001), Psacharopoulos, and Hanushek and Kimko are biased by mismeasurement, Wößmann's measure will also be biased.

2.4.5 Summary of education-based measures

Education-based measures of human capital, including literacy rates, school enrolment rates and average years of schooling, are easy to quantify and have good international data coverage. These measures give a rough idea of how much human capital a country has. However, they have been criticised for not adequately reflecting key aspects of human capital and for emphasising quantity over quality. By being based upon some crude proxy for education so far experienced, these measures neither capture the richness of knowledge embodied in humans nor quantify the flow of future benefits of the knowledge accrued. Indeed, they have been found to be at best relevant to one group of countries but not to another group that is at a different stage of development.

The use of these indicators has also been hampered by deficiencies in the data. Recently, ample evidence has been gathered which shows that it is how they are measured, rather than what they measure, that renders these indicators poor proxies for the true stock of human capital.

Although Barro and Lee (1996, 2001) and Lee and Barro (2001) account for quality of schooling, their method has complicated the matter. Since quality is multidimensional, many indicators of quality have to be considered, yet estimates across indicators are very poorly correlated. Hanushek and Kimko (2000) combine several test scores in an index of schooling quality and Wößmann (2003) incorporates this indicator, together with average rates of returns to education, in a comprehensive quality-adjusted measure of human capital. However, as with pure quantity measures of schooling, errors in recording data and imputing missing data on the quality indicators are a potential source of bias. Given the dubious quality of his data, the reliability of Wößmann's estimates of human capital is not warranted.

2.5 The integrated approach

Recognising that no single approach to human capital measurement is free from limitations, some researchers combine different methods in order to exploit their strengths and neutralise their weaknesses.

Tao and Stinson (1997) integrate the cost and income methods. They note that investments in human capital determine the human capital stock, which can be established by the cost method. Human capital, in turn, determines

earnings through the income-based approach:

$$Y_{s,a,e} = w_t h_{s,a,e} \tag{2.20}$$

where h and Y are respectively human capital and earnings, s, a and e denote the sex, age and education level of an individual, and w_t is the human capital rental rate in year t.

Since both of the right-hand side variables are unobservable, one of them must be standardised. Tao and Stinson choose to standardise the human capital stock of base entrants. This group is selected because they enter the labour force straight after leaving high school, thus no allowance needs to be made for the impact that experience, on-the-job training and the cost of training have on their human capital. The ability of these base entrants can be determined from the Scholastic Aptitude Test (SAT) scores. This test provides a consistent measure of the ability of high school graduates and SAT results are available for many years.[14]

The human capital stock of base entrants is estimated as the accumulated real expenditures on their general education. Once the human capital of these individuals is defined, the human capital rental rate w can be estimated by applying earnings data to equation (2.20). That rental rate, which is assumed to be constant across cohorts, can then be plugged into equation (2.20), together with earnings, to derive the human capital stock for other cohorts.

It is found that the human capital stock of the US employed work force expanded sixfold between 1963 and 1988. When differences in the abilities of

[14]The SAT data suffer from a self-selection bias, since students have the choice whether or not to take the test. Tao and Stinson have, however, corrected for this problem.

base entrants are considered, specifically, when entry-level wages are assumed to match the SAT scores of base entrants, the growth reduced to less than 100 percent. The increase was greater for females (135%) than for males (75%), largely due to rising labour supply by the former.

Tao and Stinson claim that by using the cost method to estimate human capital for only base entrants, their framework avoids the problem of what constitutes an investment in human capital in the population. Besides, this approach requires no assumptions about depreciation in human capital. However, a problem of the cost method remains unsettled. Specifically, how good are educational expenses at measuring the human capital of base entrants? Moreover, this model assumes that base entrants are paid according to their ability as measured by the SAT score, but whether or not SAT scores are a good indicator of ability is open to question.

Also combining various methods, Dagum and Slottje (2000) define human capital as a dimensionless latent variable:

$$z = L(x_1, x_2, x_3, \ldots, x_p) \tag{2.21}$$

where z is a standardised (zero mean and unit variance) human capital latent variable, and x_1, x_2, x_3, $\ldots$, x_p are standardised indicators of human capital. An accounting value of human capital for the ith economic unit is given as:

$$h_i = e^{z_i} \tag{2.22}$$

Dagum and Slottje then adopt Jorgenson and Fraumeni's (1989) method to estimate H_x, the human capital of the average economic unit aged x. The monetary value of human capital of the ith sample observation is:

$$H_i = h_i \frac{\overline{H}}{\overline{h}} \tag{2.23}$$

where $\overline{h}$ and $\overline{H}$ are respectively the average values of h_i and H_x. Intuitively, the monetary value of a person's human capital is equal to the average lifetime earnings of the population, weighted by the level of human capital that he has relative to the average human capital of the population.

Dagum and Slottje estimate that per capita human capital ranged from \$239,000 to \$365,000 in 1982, depending on the choices of the discount rate and the economic growth rate. In real terms, their lowest estimate is still twice Kendrick's (1976) estimate for 1969, yet they are only a fraction of those obtained by Jorgenson and Fraumeni (1989, 1992) because the latter incorporate non-market human capital.

While previous studies only estimated average human capital of cohorts, Dagum and Slottje are able to estimate the human capital of individuals. Theoretically, the latent variable approach can remove the omitted variable bias of the income-based method. However, this innovation is hampered by the lack of data on intelligence, ability, or hard work. Besides, their model assumes a standardised normal distribution of human capital; whether or not human capital is normally distributed is controversial. Furthermore, as with the income-based method, results obtained from this integrated framework

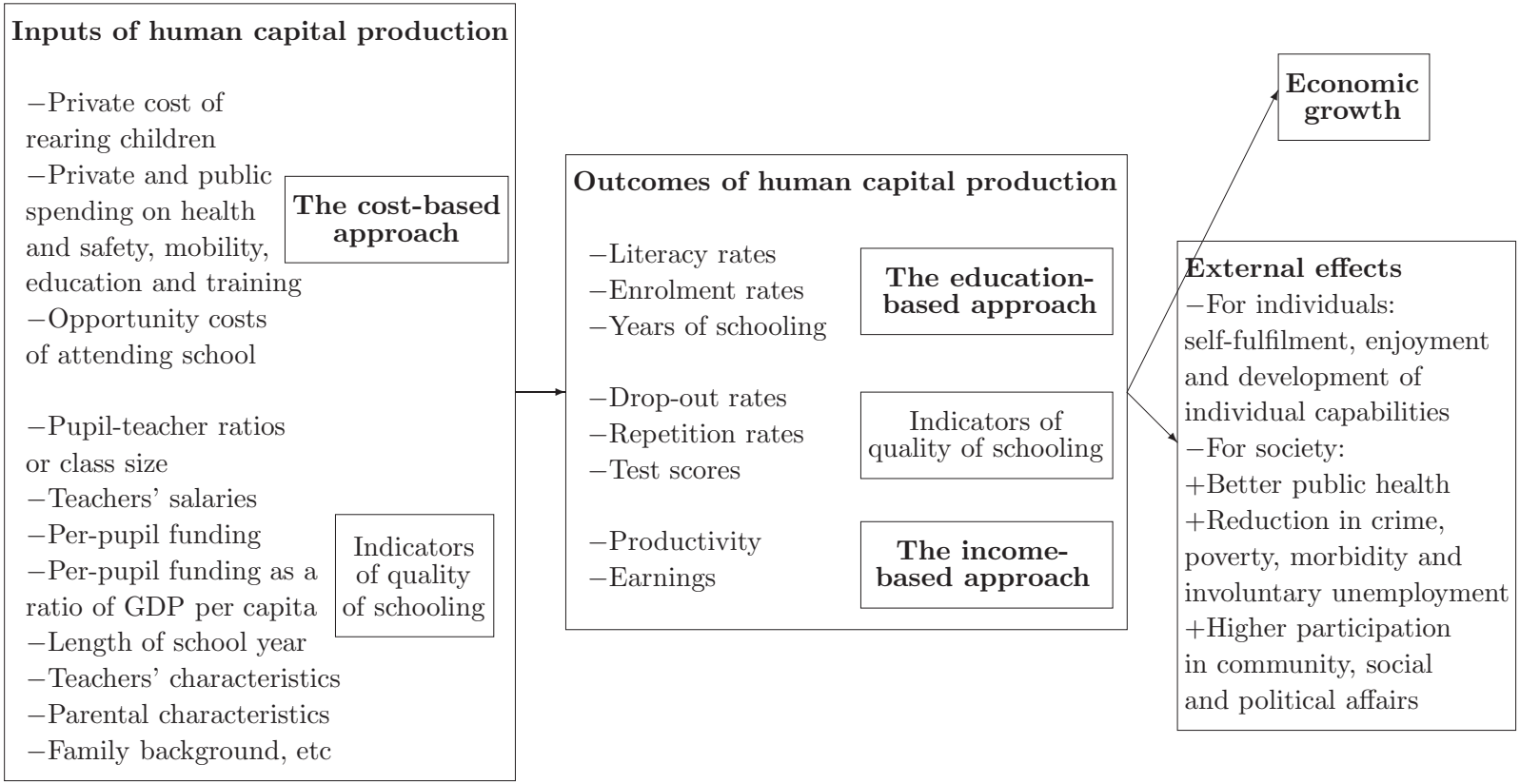
are very sensitive to assumptions regarding the retirement age, discount rate and real income growth rate.

2.6 Summary of approaches to human capital measurement

Different as they may seem, the cost-, income- and education-based approaches are not unrelated. Figure 2.1 shows how these models are connected. In words, inputs in the human capital production process, such as costs of rearing and educating people, form the basis for the cost method. The income method builds on individuals' earnings, whereas such indicators as literacy rates, school enrolment rates and average years of schooling have widely been used as education-based measures of human capital.

There has been a radical change in the motivation behind human capital valuation. Early studies were more concerned with demonstrating the power of a nation, with estimating the money values of human loss from wars and plagues, and with developing accurate measures of human wealth in national accounts. Recently, the focus has switched to using human capital as a tool to explain economic growth across countries. Human capital is believed to play a critical role in the growth process, as well as producing positive external effects such as enhanced self-fulfilment, enjoyment and development of individual capabilities, reduction in poverty and delinquency, and greater participation in community and in social and political affairs.

Figure 2.1: Human capital production and common approaches to human capital measurement



However, the impact of human capital on economic growth has not been empirically supported. The lack of empirical consensus arises because approaches to human capital valuation build on sound theoretical underpinning, yet none of them is free from shortcomings. Each approach is more or less subject to two types of measurement error: the measure does not adequately reflect key elements of human capital, and data on the measure are of poor quality. Therefore, properly measuring human capital remains a challenge.

2.7 Recent New Zealand studies

Most published research on human capital in New Zealand has dealt with either changing prices – the returns to particular educational qualifications (Maani, 1999) – or changing quantities, such as the compositional shift implied by the rising importance of the 'information workforce' (Engelbrecht, 2000). There are also many studies that use proxy indicators within the education-based approach, such as New Zealand Treasury (2001).

Recently, there has been considerable interest in directly valuing human capital. Hendy et al. (2002) examine how the value of human capital changed during 1986-1996. Whilst their method is also based on an expected income concept, it does not take into account enrolment in further education and survival probabilities. Their study shows that the value of the human capital of the employed workforce rose by 11.7 percent between 1991 and 1996, after falling by 1 percent over the previous five years. Overall, employment growth produced 7.3 of the 10.6 percent increase in human capital, which was then

offset by a drop in productivity of 0.4 percentage points. The remaining 3.7 percentage points were attributed to relative quantity and relative price effects.

In a related paper, Hyslop et al. (2003) find that the value of human capital rose by 20 percent between 1986 and 2001. Around 75 percent of this growth was caused by general increases in incomes across qualifications at constant qualification shares, the effects of upskilling at constant incomes accounted for 15-20 percent, and 8 percent was left to be explained by the interaction of upskilling and rising incomes. Evidence at the individual qualification level suggests that the upskilling seems to have been driven by the increase in demand for skills. As with Hendy et al. (2002), Hyslop et al.'s can be seen as a measure of the current 'flow' (based on average annual earnings), rather than 'stock' (based on lifetime earnings), of human capital.

The work that is closest in spirit to mine is Oxley and Zhu (2002). They use census data in five-year age bands to estimate expected lifetime income. However, there is no differentiation amongst workers according to their educational attainment, labour-force status or source of income. Oxley and Zhu find that human capital averaged $282,000 per person in 1996. This figure reflected an increase of 7.7 percent from 1986, most of which (6.3%) occurred between 1986 and 1991. Some degree of catching-up by females is also evident, although women still have no more than 60 percent as much human capital as men do. The current study will present more detailed makeup of the stock of human capital based on more disaggregated data and differing assumptions about cross-sectional variables.

Chapter 3

An application of Jorgenson and Fraumeni's approach

3.1 Models

The first approach that I use to estimate human capital is adopted from Jorgenson and Fraumeni (1992), as described in Section 2.3.4. Here, I modify the model to suit the New Zealand context and data. Unlike Jorgenson and Fraumeni, I ignore the contribution that employed individuals make outside work (and outside what would be 'working hours,' for non-workers). The wage rate and employment rate for non-participants are unobservable; similar to Jorgenson and Fraumeni, I assign to these individuals the human capital value that similarly characterised people have. Formally, average human capital h, defined as the present value of lifetime labour income, of all individuals aged a with education level e_i, is specified as:

$$h_a^{e_i} = W_a^{e_i} Y_a^{e_i} + S_{a,a+1}^{e_i} h_{a+1}^{e_i} d \tag{3.1}$$

where:

$W =$ employment rate;

$Y =$ average annual labour income of workers;

$S_{a,a+1} =$ probability of surviving one more year from age a;

$d =$ $(1+g)/(1+i)$;

$g =$ annual growth rate in real income;

$i =$ discount rate.

The model holds separately for each gender. I assume that the potential working life extends from 18 to 64, a common age range of the work force in developed countries. There are four levels of educational attainment: (1) unskilled (no more than School Certificate), (2) non-degree (including all post-school, non-degree qualifications), (3) Bachelors degree and (4) post-graduate. I apply a growth rate of 1.5 percent and a discount rate of 6 percent; these figures are in line with New Zealand's economic reality in the period studied.[15]

While equation (3.1) is likely to hold for most of the population over most of their working life, there are people enrolled in further study who, in the context of the model, are trying to jump onto a higher age-earnings profile. When the model allows further study, individuals face two possible earnings streams; one with continuous work and the other with the possibility of delaying work for further education. Hence, lifetime labour incomes for any

[15] According to the Reserve Bank of New Zealand (2005), growth in real GDP per capita averaged 0.7% per annum in the 1984-1994 period, rising to 2.2% in 1994-2004.

given cohort are a linear combination of these two earnings streams, where the weights depend on the probability of enrolment:

$$H_a^{e_i} = W_a^{e_i} Y_a^{e_i} + \{(1 - E_a^{e_i}) S_{a,a+1}^{e_i} h_{a+1}^{e_i} + E_a^{e_i} S_{a,a+1}^{e_j} h_{a+1}^{e_j}\} d$$
$$- \sum_{m=1}^{K^{i,j}-1} \Big(\sum_{k=1}^{K^{i,j}-m} E_a^{k(i,j)} \Big) (S_{a,a+m}^{e_j} W_{a+m}^{e_j} Y_{a+m}^{e_j} - S_{a,a+m}^{e_i} W_{a+m}^{e_i} Y_{a+m}^{e_i}) d^m \quad (3.2)$$

where:

$H =$ per capita human capital that incorporates the effect of further education;

$E^{e_i} =$ proportion of the population who are studying for a higher qualification;

$E^{k(i,j)} =$ proportion of the population undertaking the $e_j > e_i$ qualification in its kth year;

$K =$ the number of years it takes to complete a qualification.

Equation (3.2) are subject to the following assumptions:[16]

- People can only study for a higher qualification than what they already have. If Bachelors degree holders study for, say, an undergraduate diploma, their extra study counts for nothing. Due to the lack of information, I assume that university students who already hold a Bachelors degree are studying towards a post-graduate qualification. No further enrolment is allowed for post-graduates, because they have reached the highest education level;

[16]The last term in equation (3.2) captures the fact that qualifications take more than a year to complete and that not all students are in their final year of study.

- A post-graduate qualification takes two years to complete, conditional on holding a Bachelors degree;
- Unskilled and non-degree qualified individuals take four and three years respectively to complete a Bachelors degree;
- The study time for a non-degree qualification is two years;
- Except for certain young ages,[17] students enrolled in any qualification that requires more than one year are evenly distributed across different study stages;
- Direct costs of study are offset by part-time earnings, so that there is no need to apply negative earnings while studying.[18]

Equation (3.2) can then be specified for each education cohort. For Bachelors degree holders:

$$\begin{aligned} H_a^{e_3} =& W_a^{e_3} Y_a^{e_3} + \{(1 - E_a^{e_3}) S_{a,a+1}^{e_3} h_{a+1}^{e_3} + E_a^{e_3} S_{a,a+1}^{e_4} h_{a+1}^{e_4}\} d \\ & - E_a^{1(3,4)} (S_{a,a+1}^{e_4} W_{a+1}^{e_4} Y_{a+1}^{e_4} - S_{a,a+1}^{e_3} W_{a+1}^{e_3} Y_{a+1}^{e_3}) d \end{aligned} \tag{3.3}$$

For non-degree qualified individuals:

$$\begin{aligned} H_a^{e_2} =& W_a^{e_2} Y_a^{e_2} + \{(1 - E_a^{e_2}) S_{a,a+1}^{e_2} h_{a+1}^{e_2} + E_a^{e_2} S_{a,a+1}^{e_3} h_{a+1}^{e_3}\} d \\ & - (E_a^{1(2,3)} + E_a^{2(2,3)}) (S_{a,a+1}^{e_3} W_{a+1}^{e_3} Y_{a+1}^{e_3} - S_{a,a+1}^{e_2} W_{a+1}^{e_2} Y_{a+1}^{e_2}) d \\ & - E_a^{1(2,3)} (S_{a,a+2}^{e_3} W_{a+2}^{e_3} Y_{a+2}^{e_3} - S_{a,a+2}^{e_2} W_{a+2}^{e_2} Y_{a+2}^{e_2}) d^2 \end{aligned} \tag{3.4}$$

[17] For example, all 18-year-old students studying for a Bachelors degree are assumed to be in their first year.

[18] This assumption bypasses the impact of student loans and of degree-specific costs on the accumulation of human capital. However, tuition fees for most degrees in New Zealand are subsidised by at least 75%. Therefore, this assumption is quite reasonable. It is also a standard assumption in studies on returns to education.

For unskilled individuals:

$$
\begin{aligned}
H_a^{e_1} &= W_a^{e_1} Y_a^{e_1} \\
&+ \{(1 - E_a^{e_1}) S_{a,a+1}^{e_1} h_{a+1}^{e_1} + E_a^{(1,2)} S_{a,a+1}^{e_2} h_{a+1}^{e_2} + E_a^{(1,3)} S_{a,a+1}^{e_3} h_{a+1}^{e_3}\} d \\
&- E_a^{1(1,2)} (S_{a,a+1}^{e_2} W_{a+1}^{e_2} Y_{a+1}^{e_2} - S_{a,a+1}^{e_1} W_{a+1}^{e_1} Y_{a+1}^{e_1}) d \\
&- (E_a^{1(2,3)} + E_a^{2(2,3)} + E_a^{3(2,3)})(S_{a,a+1}^{e_3} W_{a+1}^{e_3} Y_{a+1}^{e_3} - S_{a,a+1}^{e_1} W_{a+1}^{e_1} Y_{a+1}^{e_1}) d \\
&- (E_a^{1(2,3)} + E_a^{2(2,3)})(S_{a,a+2}^{e_3} W_{a+2}^{e_3} Y_{a+2}^{e_3} - S_{a,a+2}^{e_1} W_{a+2}^{e_1} Y_{a+2}^{e_1}) d^2 \\
&- E_a^{1(2,3)} (S_{a,a+3}^{e_3} W_{a+3}^{e_3} Y_{a+3}^{e_3} - S_{a,a+3}^{e_1} W_{a+3}^{e_1} Y_{a+3}^{e_1}) d^3
\end{aligned}
\tag{3.5}
$$

3.2 Data

I use data from each Census of Population from 1981 to 2001. The data are in the form of population counts within homogeneous cells classified by age, gender, education level, employment status and income bracket. I form the data into 366 cohorts defined by 47 ages (18-64), 2 genders and 4 education levels.[19]

Table 3.1 shows the distribution of the working-age population by gender and education. The share of university graduates increased sharply, from 4.1 percent in 1981 to 12 percent in 2001. Notably, the gender gap in education has almost disappeared.

Table 3.2 (page 75) presents the labour-force participation rate and employment rate. The share of labour-force participants rose by 6.8 percentage points between 1981 and 2001, while the probability of employment dropped by 3.1 percentage points. Women at all education levels are increasingly

[19]Some combinations do not exist (eg. 18-year-old Bachelors).

Table 3.1: Distribution of the working-age population

	1981	1986	1991	1996	2001
Male					
Unskilled	30.5	24.8	22.3	26.0	22.5
Non-degree	17.0	21.5	23.2	18.2	20.2
Bachelors	2.1	2.3	2.7	3.4	3.9
Post-graduate	0.6	1.5	1.5	1.8	2.0
Sub-total	50.2	50.1	49.8	49.3	48.7
Female					
Unskilled	34.2	30.2	26.8	28.2	23.5
Non-degree	14.2	17.4	20.4	18.2	21.7
Bachelors	1.2	1.5	2.0	3.0	4.3
Post-graduate	0.2	0.8	1.0	1.3	1.8
Sub-total	49.8	49.9	50.2	50.7	51.3
Total number (thousand)	1,805.4	1,941.6	2,041.1	2,204.6	2,278.0
Change from last census		7.5	5.1	8.0	3.3

Source: New Zealand Census of Population, 1981, 1986, 1991, 1996, 2001.
Note: The population base is ages 18-64. Entries are percentages unless otherwise stated.

likely to be in employment or seeking jobs. By contrast, the probability of men partaking in the labour force declined drastically during those 20 years.

Since New Zealand Censuses do not collect data on earnings, I use (gross) income as a proxy for earnings. Income in New Zealand Censuses counts all sources (except for Census 1981 which excludes superannuation). Hopefully by using only the income of employees, for whom earnings are likely to predominate, I eliminate obvious biases. The annual income for paid employees is applied to employers and self-employed persons with the same gender-education-age profile. This adjustment keeps the focus on the price of labour services, because the reported income of employers and self-employed people may include returns to non-labour inputs. Since the data are categorical, I use the mid-point of the closed intervals. For the open-ended interval at

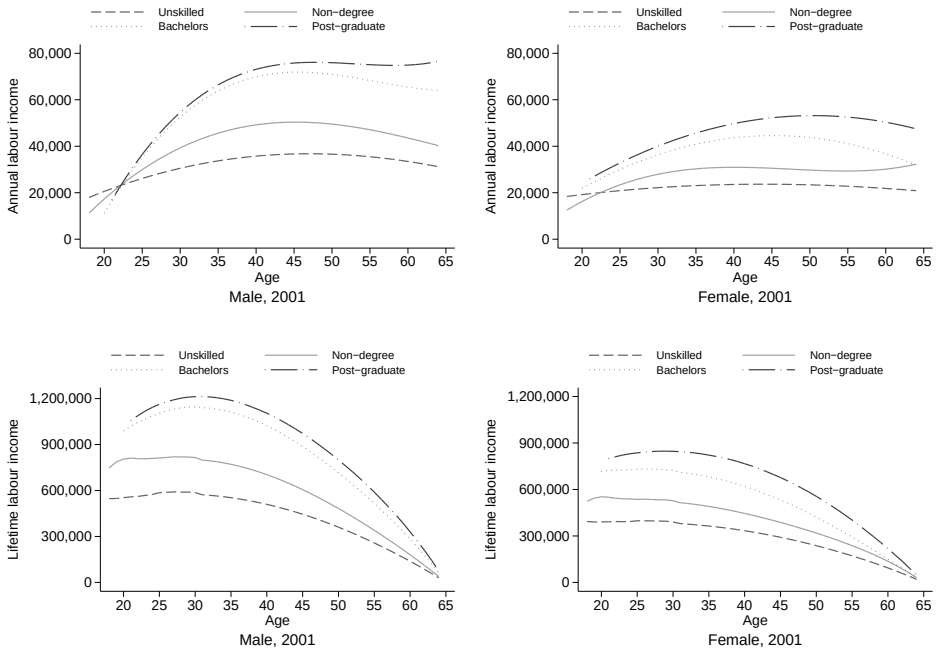
the top of the income distribution (e.g. >$100,000) the mean income is set at 30 percent above the lower bound, while for the lowest income interval it is 80 percent of the upper bound (recommended by Chen et al. (1991)). I distribute those who did not specify their income evenly across the income ranges.

Table 3.3 (page 76) shows that average real income fell slightly from 1981 to 1986 but the trend has since reversed. This trend, however, is not universal. Over the 20-year period, unskilled individuals saw their real income stagnate, but the rest of the work force experienced rising income. There is a large income gap between university graduates and the less educated, and this gap has widened. Income profiles are steeper for males and for tertiary degree holders (see Figure 3.1 for 2001).[20]

Enrolment data in the Census have several deficiencies. In particular, the last three censuses did not collect information on whether or not a person was studying for a qualification. Although the 1986 Census asked about student status, it did not ask for the type of qualification one was studying for; therefore, I am unable to determine whether or not an enrolee was studying to improve his education profile. The 1981 Census is the only one to contain relatively satisfactory information on enrolment. Although the model can still be run on zero enrolment, these estimates do not take into account the fact that some people withdraw from the labour force and study for a higher qualification because they expect their earnings to improve consequently. If

[20]The volatility in the profiles for university graduates is due to the small population size of each cohort.

Figure 3.1: Annual and lifetime labour incomes



the effect of enrolment is ignored, students' potential to contribute to the country's human capital stock will not be adequately captured.

Since the most recent three censuses did not ask about student status, I have to turn to another question for enrolment rates. In particular, enrolment is defined as attending study or training courses in the last week (Census 1991), attending/studying for a course at school or anywhere else in the last 7 days (Census 1996), or attending/studying for more or less than 20 hours per week at school or any other places in the last 4 weeks (Census 2001). I only consider full-time study and training, to be consistent with the 1981 and 1986 Censuses. Those who were attending full-time study or training courses over the last week (or, in Census 2001, 4 weeks) were also more likely to be students.

Census 1981 is the only one to give enrolment information by current level of study, so I apply the enrolment *pattern* from this census to the enrolment *rates* (by existing qualification) for the other censuses. For example, if 80 percent of students from the non-degree group were attending university in 1981, I assume that 80 percent of enrolees from the non-degree group in other census years were studying for a degree, while letting the overall enrolment rate fluctuate from census to census.[21] I cut off the work-study phase at age 30 because educational enrolment beyond that age is negligible.

Data for the last variable, survival rates, are obtained from *New Zealand Life Tables*. Even though education tends to reduce mortality rates, the available data are only broken down to gender and age, so I assume that the probabilities of surviving do not vary with education. This assumption would understate differences in lifetime income between education levels, yet I believe that the resulting bias is trivial.[22]

3.3 Basic results

Table 3.4 (page 76) reports the baseline estimates, and the results for 2001 are also displayed in the bottom panels of Figure 3.1 on the facing page. Lifetime income increases until somewhere around ages 25-30, after which it falls steadily. The peak in lifetime income occurs some 10 years earlier for women than for men. A similar lag is also observed between university

[21] 'Unskilled' includes those who have no more than a School Certificate, so in New Zealand they can not enrol for a degree before reaching 25.

[22] As noted in Le et al. (2006), when equal survival probabilities are assumed between men and women, the ratio of average lifetime income between the two genders changes marginally, from 56.9% to 56.4%.

graduates and non-graduates. This is because the time devoted to further education postpones reaping the higher returns until older ages.

The shape of annual income profiles greatly influences lifetime income profiles. Lifetime income profiles are flatter for females than for males, and also flatter for unskilled and non-degree qualified people than for graduates, reflecting what was observed earlier about annual income profiles.

While average annual income in 2001 was 14 percent higher than in 1981, the difference in lifetime income is only 10 percent. This disparity can be explained by changes in employment rates. While annual income shrank by 2.4 percent in real terms between 1981 and 1986, lifetime income fell by 3.8 percent, due to a drop of 2 percentage points in the employment rate. This is also the only inter-censual decrease in per capita human capital. Between 1986 and 1991, the employment rate fell by 4 percentage points, but annual income grew more than enough to offset it, and as a result lifetime income increased by 3.7 percent. Since 1991, both employment and real annual income have risen, improving lifetime income consequently.

The value of the stock of human capital is presented in Table 3.5 (page 77). The share of unskilled individuals in the stock of human capital fell from one half of the male total in 1981 to just one third in 2001, and the proportionate decline is even greater for women. By contrast, the human capital contributed by university graduates has increased, in both relative and absolute terms. Indeed, this is to be expected, as annual income of these people improved relatively the most and that their share of the population also grew. For example, in 1991, when the total human capital stock increased by a mere 9.1 percent from 1986, the capital accounted for by degree hold-

ers rose by 30 percent. While total human capital increased by 39 percent, university graduates' capital almost quadrupled over the period 1981-2001. Women contribute 36-41 percent to the country's human capital. This follows directly from the fact that women's average earnings are only two thirds of men's.

3.4 Sensitivity analysis

Table 3.6 (page 77) reports the effects of varying some modelling assumptions. Changing the discount and growth rates to the values used by Jorgenson and Fraumeni (1992) would raise the value of the human capital stock by 15 percent yet leaving the pattern across census years unaffected. A bigger change comes from excluding ages 18-24, which reduces the stock of human capital by 19 percent and lowers the per capita lifetime income by 5 percent. Lengthening the study time for each qualification by one year produces an insignificant negative effect. Ignoring the impact of enrolment would lower the stock of human capital by 1.4 percent but understate average lifetime labour income by 4.1 percent for those in the 'study' age range (individuals younger than 30 and not holding a post-graduate qualification). The age of retirement is an important determinant of human capital; if it is set at 60 rather than 65, a 12 percent decrease in the estimated human capital would result.

The Jorgenson and Fraumeni method assumes that individuals make a decision over hours of work such that the marginal value of work equals that of leisure and hence non-market human capital should be evaluated at the wage

rate. If non-market human capital is excluded, the estimated value of human capital would fall by 20 percent. That extra capital can *potentially* be useful, but it is currently idle. It is hard to see why idle capital has the same value as working capital, when the former is not generating output. Consider an example of two groups, each having 100 individuals. Ninety people in the first group participate in the labour force, 65 of whom are employed. In the second group, 49 out of the 50 participants are in employment. The second group has a higher employment rate, so other things being equal, it would have a higher value of human capital, as estimated by the Jorgenson and Fraumeni model. But non-participation can be a form of unemployment (Murphy and Topel, 1997). Even when participation is a choice, non-participants opt out of economic production, their human capital is, therefore, of little economic value. Some non-market activities, such as parenting and do-it-yourself, are economically valuable. Yet, outside work and 'maintenance' (ie. sleeping and eating), most of people's time is devoted to leisure. In other words, most of non-market time is for *consumption*, and therefore the contribution by non-labour-force participants to the country's *productive* capacity is limited. The effect of not imputing non-market human capital will be explored in the next chapter.

Table 3.2: Labour-force participation and employment rates

	Labour-force participation					Employment				
	1981	1986	1991	1996	2001	1981	1986	1991	1996	2001
Male										
Unskilled	91.3	87.5	76.8	75.7	76.2	95.6	94.8	87.2	91	91.4
Non-degree	90.8	91.5	86.6	88.2	87.3	98	97	91.9	95.1	94.7
Bachelors	91.5	93.4	90.9	92	91.8	98	97.3	94.3	95.1	95.9
Post-graduate	94.1	95.2	93.5	92.6	92.5	98.8	98.3	96.7	95.5	96.4
Weighted average	91.2	89.7	82.6	82.1	82.7	96.6	96	90.3	93.2	93.5
Female										
Unskilled	42.6	57.8	53.9	59.1	60.9	95	91.1	89	90.5	90.8
Non-degree	56.6	72.5	71.7	76.6	75.6	96.6	93.7	90.6	93.8	93.4
Bachelors	62	78.3	78.6	82.7	83.4	95.3	94.1	92.6	94.6	95.6
Post-graduate	62.1	81.9	83.8	85.1	86.3	95.8	96.2	95.1	95.2	96.2
Weighted average	47.1	63.9	62.7	67.5	69.9	95.6	92.3	90.1	92.3	92.7
Overall average	69.3	76.9	72.6	74.7	76.1	96.1	94.1	90.1	92.6	93
Total number (million)	1.25	1.49	1.48	1.65	1.73	1.2	1.41	1.34	1.53	1.61
Change from last census		19.4	-.654	11	5.37		17.1	-5.15	14.2	5.73

Note: See Table 3.1 (page 68).

Table 3.3: Real annual income for employees

	1981	1986	1991	1996	2001
Male					
Unskilled	31.2	30.5	31.0	33.5	32.8
Non-degree	36.9	37.2	38.1	40.1	41.2
Bachelors	48.3	48.7	53.8	56.1	59.3
Post-graduate	56.3	56.8	62.6	65.9	67.5
Weighted average	34.2	35.2	37.1	39.3	40.6
Female					
Unskilled	20.5	18.4	19.9	22.3	22.7
Non-degree	24.6	23.3	24.9	25.9	27.2
Bachelors	31.7	30.1	33.9	34.1	37.4
Post-graduate	39.4	34.8	40.1	41.9	46.1
Weighted average	22.4	21.2	23.5	25.3	27.3
Overall average	30.2	29.5	31.2	32.9	34.4
Change from last census (%)		-2.4	5.8	5.4	4.5

Note: Estimates are in 2001 thousand dollars, converted using the Prevailing Weekly Wage Index PWIQ.S4329 and All Salary & Wage Rates LCIQ.SA53Z9. In 2001, NZ$1 exchanged for US$0.44 in nominal terms, or US$0.68 in PPP terms.

Table 3.4: Per capita lifetime labour income

	1981	1986	1991	1996	2001
Male					
Unskilled	447.8	443.4	416.0	457.5	430.7
Non-degree	634.1	593.1	592.0	659.7	648.0
Bachelors	894.9	878.6	909.2	938.7	931.1
Post-graduate	908.3	873.2	910.3	975.0	949.2
Weighted average	535.3	540.5	540.1	583.8	582.7
Female					
Unskilled	290.8	245.5	258.5	290.4	279.6
Non-degree	435.3	372.4	401.7	435.1	433.6
Bachelors	611.5	523.3	580.2	588.1	621.9
Post-graduate	625.8	554.4	608.6	644.2	703.3
Weighted average	341.0	302.9	336.5	369.0	388.0
Overall average	438.6	422.0	437.8	474.9	482.8
Change from last census (%)		-3.8	3.7	8.5	1.7

Note: See Table 3.3.

Table 3.5: Value of the human capital stock

	1981	1986	1991	1996	2001
Male					
Unskilled	246.5	213.5	189.2	261.9	221.2
Non-degree	194.8	247.8	280.9	264.0	298.8
Bachelors	34.0	39.7	50.6	70.4	83.5
Post-graduate	10.0	24.9	27.7	38.3	43.1
Sub-total	485.3	526.0	548.5	634.5	646.5
Female					
Unskilled	179.4	144.0	141.4	180.5	149.9
Non-degree	111.8	125.8	167.6	174.8	214.2
Bachelors	12.8	14.8	24.1	38.6	61.1
Post-graduate	2.5	8.8	12.0	18.6	28.1
Sub-total	306.5	293.4	345.1	412.5	453.3
Total	791.8	819.4	893.6	1,047.0	1,099.9
Change from last census (%)		3.5	9.1	17.2	5.0

Note: Estimates are in 2001 billion dollars.

Table 3.6: Sensitivity analysis on human capital estimates

	Per capita		Aggregate stock	
	Estimate ($thousand)	Change relative to baseline (%)	Estimate ($billion)	Change relative to baseline (%)
(1) **Baseline**	482.8		1,099.9	
(2) Lengthening study time[a]	482.8	-.014	1,099.7	-.014
(3) Ignoring enrolment[b]	476.2	-1.38	1,084.7	-1.38
(4) $g = 1.32\%$ and $i = 4.58\%$[c]	553.5	14.6	1,261.0	14.6
(5) Ages 25-64 only	458.9	-4.96	887.4	-19.3
(6) Ages 18-59 only	511.6	5.95	1,086.3	-1.23
(7) (6) & retirement age = 60[d]	451.3	-11.8	958.3	-11.8
(8) Ignoring non-market effects[e]	384.1	-20.4	875.1	-20.4

Note: All estimates refer to year 2001.
[a] Lengthening study time for each qualification by one year.
[b] Applying equation (3.1) to all individuals. [c] These rates were used by Jorgenson and Fraumeni (1992). [d] Change is relative to (6). [e] Assuming zero contribution from non-labour-force participants.

Chapter 4

A revised model for estimating human capital

4.1 Models

Jorgenson and Fraumeni's (1989,1992) model assumes that in t years people will earn as much as what is currently earned by those who are now t years older but otherwise have the same characteristics, adjusted for a constant rate of growth in real income. In Chapter 3, I applied an annual growth rate of 1.5 percent to all cohorts and periods. This, however, did not prove appropriate. For example, Table 4.1 shows that average real income dropped by 2.4 percent between 1981 and 1986, or by 0.5 percent a year, and the change varied markedly from cohort to cohort (see Appendix Figure 1).

In this chapter, I assume that the expected earnings in t years of the cohort (s, e, a) are the observed earnings of the cohort $(s, e, a + t)$ in year $y + t$. That is, growth rates in earnings vary by gender-education-age cohort,

Table 4.1: Relative changes in average real income

	1981-86	1986-91	1991-96	1996-2001
Male				
Unskilled	-2.2	1.6	8.1	-2.1
Non-degree	0.6	2.4	5.2	2.9
Bachelors	0.7	10.6	4.2	5.8
Post-graduate	0.9	10.2	5.3	2.4
Weighted average	2.8	5.4	5.9	3.4
Female				
Unskilled	-10.3	8.2	12.0	1.7
Non-degree	-5.3	7.0	3.7	5.3
Bachelors	-5.0	12.6	0.4	9.9
Post-graduate	-11.7	15.3	4.5	9.9
Weighted average	-5.6	11.3	7.5	8.0
Overall average	-2.4	5.8	5.4	4.5

Note: Entries are percentages. Nominal values of income are deflated using the Prevailing Weekly Wage Index PWIQ.S4329 and All Salary & Wage Rates LCIQ.SA53Z9.

and these growth rates are what is observed in reality. Besides, I account for inter-temporal growth in employment rates and survival probabilities. While Jorgenson and Fraumeni evaluate the human capital of non-workers at the wage rate, I assume that the value of non-participants' human capital is *effectively* zero.

I also make a first attempt to account for ethnicity. Ethnicity is an interesting policy issue in New Zealand. Unlike other developed countries which are composed of a generic European group and a few migrant, non-European minorities, New Zealand has a sizeable indigenous population, the Māori, who often lag behind in many social aspects. According to the 2001 Household Savings Survey, for example, the average net worth (ie. assets less liabilities) of Māori households is only one third that of their European coun-

terparts (Statistics New Zealand, 2002). Even though there is considerable controversy over how ethnicity is defined, a wealth gap between ethnic groups is always evident. Differences in human capital across ethnicities would be interesting from the policy point of view.

The formal model would then become:

$$H^{y}_{e_i,a} = W^{y}_{e_i,a} Y^{y}_{e_i,a} + \sum_{t=1}^{A-a} S_{a,a+t} W^{y+t}_{e_i,a+t} Y^{y+t}_{e_i,a+t} / (1+i)^t \tag{4.1}$$

where:

$W =$ probability of engaging in paid work, defined as the number of employed people over the population, or equivalently the employment rate times the labour-force participation rate;

$y =$ current year;

$y + t =$ t years from now;

$A =$ highest age in the labour force;

$S_{a,a+t} =$ probability of surviving t more years from age a;

$S_{a,a+t} =$ $S_{a,a+t-1}(1 + s_{a+t-1})^{t-1} S_{a+t-1,a+t}$;

$s_{a+t-1} =$ annual growth rate in the next $t-1$ years of survival probabilities for age cohort $a + t - 1$.

The model holds separately for each ethnic-gender group. Equation (4.1) can be extended to allow for further study:

$$
\begin{aligned}
H^{y}_{e_i,a} &= W^{y}_{e_i,a} Y^{y}_{e_i,a} + \sum_{t=1}^{A-a} S_{a,a+t} W^{y+t}_{e_i,a+t} Y^{y+t}_{e_i,a+t} / (1+i)^t \\
&+ E_{e_i,a} \sum_{t=1}^{A-a} S_{a,a+t} \{ W^{y+t}_{e_j,a+t} Y^{y+t}_{e_j,a+t} - W^{y+t}_{e_i,a+t} Y^{y+t}_{e_i,a+t} \} / (1+i)^t \\
&- \sum_{m=1}^{K^{i,j}-1} (\sum_{k=1}^{K^{i,j}-m} E^{k(i,j)}_{a}) S_{a,a+m} \{ W^{y+m}_{e_j,a+m} Y^{y+m}_{e_j,a+m} - W^{y+m}_{e_i,a+m} Y^{y+m}_{e_i,a+m} \} / (1+i)^m
\end{aligned}
\tag{4.2}
$$

Similar to equation (3.2), the last term in (4.2) accounts for the fact that not all students finish their study in the next year. With the same assumptions about study time as in Chapter 3, equation (4.2) can be specified for each education cohort. For Bachelors degree holders:

$$
\begin{aligned}
H^{y}_{e_3,a} =& W^{y}_{e_3,a} Y^{y}_{e_3,a} + \sum_{t=1}^{A-a} S_{a,a+t} W^{y+t}_{e_3,a+t} Y^{y+t}_{e_3,a+t} / (1+i)^t \\
&+ E_{e_3,a} \sum_{t=1}^{A-a} S_{a,a+t} \{ W^{y+t}_{e_4,a+t} Y^{y+t}_{e_4,a+t} - W^{y+t}_{e_3,a+t} Y^{y+t}_{e_3,a+t} \} / (1+i)^t \\
&- E^{1(3,4)}_{a} S_{a,a+1} \{ W^{y+1}_{e_4,a+1} Y^{y+1}_{e_4,a+1} - W^{y+1}_{e_3,a+1} Y^{y+1}_{e_3,a+1} \} / (1+i)
\end{aligned}
\tag{4.3}
$$

For non-degree qualified individuals:

$$
\begin{aligned}
H^{y}_{e_2,a} &= W^{y}_{e_2,a} Y^{y}_{e_2,a} + \sum_{t=1}^{A-a} S_{a,a+t} W^{y+t}_{e_2,a+t} Y^{y+t}_{e_2,a+t} / (1+i)^t \\
&+ E_{e_2,a} \sum_{t=1}^{A-a} S_{a,a+t} \{ W^{y+t}_{e_3,a+t} Y^{y+t}_{e_3,a+t} - W^{y+t}_{e_2,a+t} Y^{y+t}_{e_2,a+t} \} / (1+i)^t \\
&- (E^{1(2,3)}_{a} + E^{2(2,3)}_{a}) S_{a,a+1} \{ W^{y+1}_{e_3,a+1} Y^{y+1}_{e_3,a+1} - W^{y+1}_{e_2,a+1} Y^{y+1}_{e_2,a+1} \} / (1+i) \\
&- E^{1(2,3)}_{a} S_{a,a+2} \{ W^{y+2}_{e_3,a+2} Y^{y+2}_{e_3,a+2} - W^{y+2}_{e_2,a+2} Y^{y+2}_{e_2,a+2} \} / (1+i)^2
\end{aligned}
\tag{4.4}
$$

For unskilled individuals:

$$
\begin{aligned}
H^{y}_{e_1,a} &= W^{y}_{e_1,a} Y^{y}_{e_1,a} + \sum_{t=1}^{A-a} S_{a,a+t} W^{y+t}_{e_1,a+t} Y^{y+t}_{e_1,a+t} / (1+i)^t \\
&+ E^{1,2}_{a} \sum_{t=1}^{A-a} S_{a,a+t} \{ W^{y+t}_{e_2,a+t} Y^{y+t}_{e_2,a+t} - W^{y+t}_{e_1,a+t} Y^{y+t}_{e_1,a+t} \} / (1+i)^t \\
&+ E^{1,3}_{a} \sum_{t=1}^{A-a} S_{a,a+t} \{ W^{y+t}_{e_3,a+t} Y^{y+t}_{e_3,a+t} - W^{y+t}_{e_1,a+t} Y^{y+t}_{e_1,a+t} \} / (1+i)^t \\
&- E^{1(1,2)}_{a} S_{a,a+1} \{ W^{y+1}_{e_2,a+1} Y^{y+1}_{e_2,a+1} - W^{y+1}_{e_1,a+1} Y^{y+1}_{e_1,a+1} \} / (1+i) \\
&- (E^{1(1,3)}_{a} + E^{2(1,3)}_{a} + E^{3(1,3)}_{a}) S_{a,a+1} \{ W^{y+1}_{e_3,a+1} Y^{y+1}_{e_3,a+1} - W^{y+1}_{e_1,a+1} Y^{y+1}_{e_1,a+1} \} / (1+i) \\
&- (E^{1(1,3)}_{a} + E^{2(1,3)}_{a}) S_{a,a+2} \{ W^{y+2}_{e_3,a+2} Y^{y+2}_{e_3,a+2} - W^{y+2}_{e_1,a+2} Y^{y+2}_{e_1,a+2} \} / (1+i)^2 \\
&- E^{1(1,3)}_{a} S_{a,a+3} \{ W^{y+3}_{e_3,a+3} Y^{y+3}_{e_3,a+3} - W^{y+3}_{e_1,a+3} Y^{y+3}_{e_1,a+3} \} / (1+i)^3
\end{aligned}
\tag{4.5}
$$

Since growth rates in earnings are not constant across ages and periods, Jorgenson and Fraumeni's recursive method no longer applies. However, the simplicity in their approach comes at the expense of biases in the results. Since growth in employment and income tends to be greater in young ages, using a common growth rate understates the inequality in human capital across ages. Jorgenson and Fraumeni's model is also unable to allow for the fact that mortality rates change over time. Their method could be an advantage in the old days when most calculations were performed by hand. Nowadays, simple estimation methods can hardly be substitutable for quality in the results. Even though equation (4.2) involves more onerous computations, it can be estimated easily with the aid of a statistical software.

4.2 Data

Since the available census data are not 'long' enough to track down income growth rates for all ages in all future periods, I use interpolation and extrapolation to fill in the gaps. For example, the expected earnings in five years for the 1981's cohort $(s_i, e_i, 21)$ is assumed to be the same as the observed earnings for cohort $(s_i, e_i, 26)$ in 1986. To work out the expected earnings for that cohort in three years (ie. in 1984) I assume that their earnings grew at a constant rate every year over the five year period. Likewise, annual growth rates observed between 1981-2001 are used to obtain expected earnings in 16-20 years for the said cohort. In cases where observed data are not available and interpolation is not possible, I 'extrapolate' by simply combining the 1996-2001 rates (see Appendix Table 7). The same approach is applied to growth rates in employment, labour-force participation and survival probabilities.

Regarding ethnicity, I first specified four groups. Generally, income, employment and labour-force participation rates are the highest for European people and the most unfavourable for non-Europeans (see Appendix Table 8 for 2001). But 'non-European,' 'mixed' and 'non-specified' groups are individually small in size, especially when further decomposed by gender, education and age. Therefore, I combine these three groups into a generic 'non-European' group. 'European' refers to those who identify themselves as belonging to European ethnic groups.[23] Due to data constraints, survival probabilities are not broken down by ethnicity. This would understate life-

[23]Some 'non-European' individuals might in fact be European, but they refused to specify their ethnicity in the census questionnaire.

time income estimates for Europeans and overstate those for non-Europeans. However, the difference should be negligible.[24]

According to Table 4.2, the share of Europeans declined over time. Eighty-five percent of the 1981 population were purely European, but this proportion dropped to 71 percent in 2001. This change is caused by the arrival of non-European migrants, cross-cultural marriages, and the fact that more and more people object to the ethnicity question.

European people are more educated than non-Europeans. In 1981, only 1.8 percent[25] of the non-European population had a tertiary degree, rising to 8.8 percent in 2001. The corresponding figures for Europeans are 4.5% and 13.2%. The share of university graduates grew consistently for each ethnic-gender group, and the extent of gender inequality in educational attainment was similar across ethnicities.

As Table 4.3 reveals, more educated people are more likely to be in employment. Previously, gender was a key determinant of employment probabilities; in 1981, 89% and 84% respectively of European and non-European men were working, compared with 46% and 43% of women. By contrast, in 2001, employment rates were more similar between genders of the same ethnicity than between ethnic groups of the same gender. For both ethnicities, the probabilities of undertaking paid work decreased for men and increased for women, primarily driven by movements in labour supply (refer back to Table 3.2). Yet the proportions of 'unskilled,' working women continue to lag far behind more educated groups.

[24]See the footnote on page 71.
[25]That is, 0.28% out of the non-European share of 15.4%.

Table 4.2: Distribution of the working-age population by ethnicity

	1981	1986	1991	1996	2001
European Male					
Unskilled	24.39	18.96	16.36	17.01	14.49
Non-degree	15.67	19.37	20.21	15.10	15.72
Bachelors	1.95	2.13	2.39	2.78	3.10
Post-graduate	0.57	1.36	1.33	1.48	1.60
Sub-total	42.58	41.81	40.28	36.37	34.91
European Female					
Unskilled	27.71	23.73	20.19	18.80	15.23
Non-degree	13.06	15.59	17.50	14.85	16.30
Bachelors	1.08	1.33	1.75	2.38	3.30
Post-graduate	0.21	0.75	0.87	1.11	1.43
Sub-total	42.07	41.41	40.31	37.14	36.26
Non-European Male					
Unskilled	6.10	5.85	5.93	8.96	8.05
Non-degree	1.35	2.15	3.04	3.05	4.53
Bachelors	0.15	0.20	0.34	0.62	0.83
Post-graduate	0.04	0.11	0.16	0.30	0.39
Sub-total	7.64	8.31	9.47	12.92	13.80
Non-European Female					
Unskilled	6.46	6.48	6.62	9.39	8.31
Non-degree	1.16	1.80	2.93	3.37	5.39
Bachelors	0.08	0.13	0.29	0.60	1.01
Post-graduate	0.01	0.06	0.10	0.20	0.32
Sub-total	7.71	8.47	9.93	13.56	15.02

Note: See Table 3.1 (page 68).

Table 4.4 (page 88) shows that there is an ethnic gap in labour income, but education remains the most important determinant. European men enjoy higher income than non-European men, who in turn make more money than European and non-European women. On average, European employees earn 25 percent more than non-Europeans, whereas the earnings ratio between post-graduates and unskilled individuals is 2 to 1.

Table 4.3: Probabilities of undertaking paid work by ethnicity

	1981	1986	1991	1996	2001
European Male					
Unskilled	88.1	85.2	73.0	78.6	79.9
Non-degree	89.4	89.2	81.3	86.5	86.8
Bachelors	90.2	91.5	86.7	91.0	91.2
Post-graduate	93.4	94.0	91.1	91.8	92.1
Weighted average	88.8	87.7	78.6	83.3	84.6
European Female					
Unskilled	40.7	54.7	52.6	61.0	64.8
Non-degree	54.4	68.2	66.8	74.8	75.5
Bachelors	58.9	74.1	74.0	82.1	83.4
Post-graduate	59.3	79.4	80.7	83.9	85.7
Weighted average	45.5	60.9	60.3	68.6	72.1
Non-European Male					
Unskilled	84.1	75.2	50.4	50.7	51.1
Non-degree	83.0	85.2	67.3	71.4	68.2
Bachelors	82.1	83.9	79.0	71.6	76.1
Post-graduate	86.7	88.6	84.9	71.9	77.3
Weighted average	83.9	78.2	57.4	57.1	59.0
Non-European Female					
Unskilled	39.6	45.2	34.0	38.4	37.9
Non-degree	57.3	65.3	53.4	59.2	55.9
Bachelors	62.4	69.0	65.6	62.4	67.7
Post-graduate	63.8	70.9	71.1	65.0	70.8
Weighted average	42.6	50.0	41.0	45.0	47.1
Overall average	66.7	72.6	65.5	69.3	70.9
Total number (million)	1.2	1.4	1.3	1.5	1.6
Change from last census		17.1	-5.1	14.2	5.7

Note: See Table 3.1 (page 68).

Table 4.4: Real annual income for employees by ethnicity

	1981	1986	1991	1996	2001
European Male					
Unskilled	32.0	31.7	32.3	35.1	34.4
Non-degree	37.3	37.8	38.9	41.3	43.3
Bachelors	48.8	49.2	55.0	58.2	62.5
Post-graduate	56.8	57.3	63.4	67.4	70.2
Weighted average	35.1	36.4	38.4	41.2	43.0
European Female					
Unskilled	20.5	18.4	20.1	22.4	22.9
Non-degree	24.7	23.4	25.1	26.2	27.9
Bachelors	32.0	30.2	34.1	34.7	38.5
Post-graduate	39.4	34.8	40.3	42.3	47.1
Weighted average	22.5	21.4	23.8	25.7	28.0
Non-European Male					
Unskilled	27.6	26.1	25.8	28.8	28.2
Non-degree	31.9	31.3	30.9	32.5	32.0
Bachelors	42.0	42.4	45.0	44.2	45.3
Post-graduate	48.4	50.5	55.1	56.4	54.7
Weighted average	28.7	28.4	29.4	31.6	32.0
Non-European Female					
Unskilled	20.8	18.3	19.1	22.0	22.0
Non-degree	24.1	22.6	23.7	24.1	24.6
Bachelors	28.1	29.1	32.6	30.9	33.3
Post-graduate	39.8	34.3	38.2	39.1	40.3
Weighted average	21.6	19.9	21.8	23.6	24.8
All European	30.9	30.3	32.1	34.1	36.0
All Non-European	26.3	25.0	26.2	28.0	28.6

Note: See Table 3.3 (page 76).

4.3 Results

New estimates of lifetime income are presented in Table 4.5. Lifetime income averaged $356,000 in 2001, reflecting a growth of 23 percent from 1981. The ethnic gaps in employment and annual income combine to create substantial, widening differences in lifetime income between ethnicities. In 1981, Europeans had 47 percent more expected lifetime income than non-Europeans, but this premium climbed to 92 percent after 20 years. Figure 4.1 displays similar patterns to those in Figure 3.1. There are more fluctuations in the income profiles of non-Europeans, due to the small size problem.

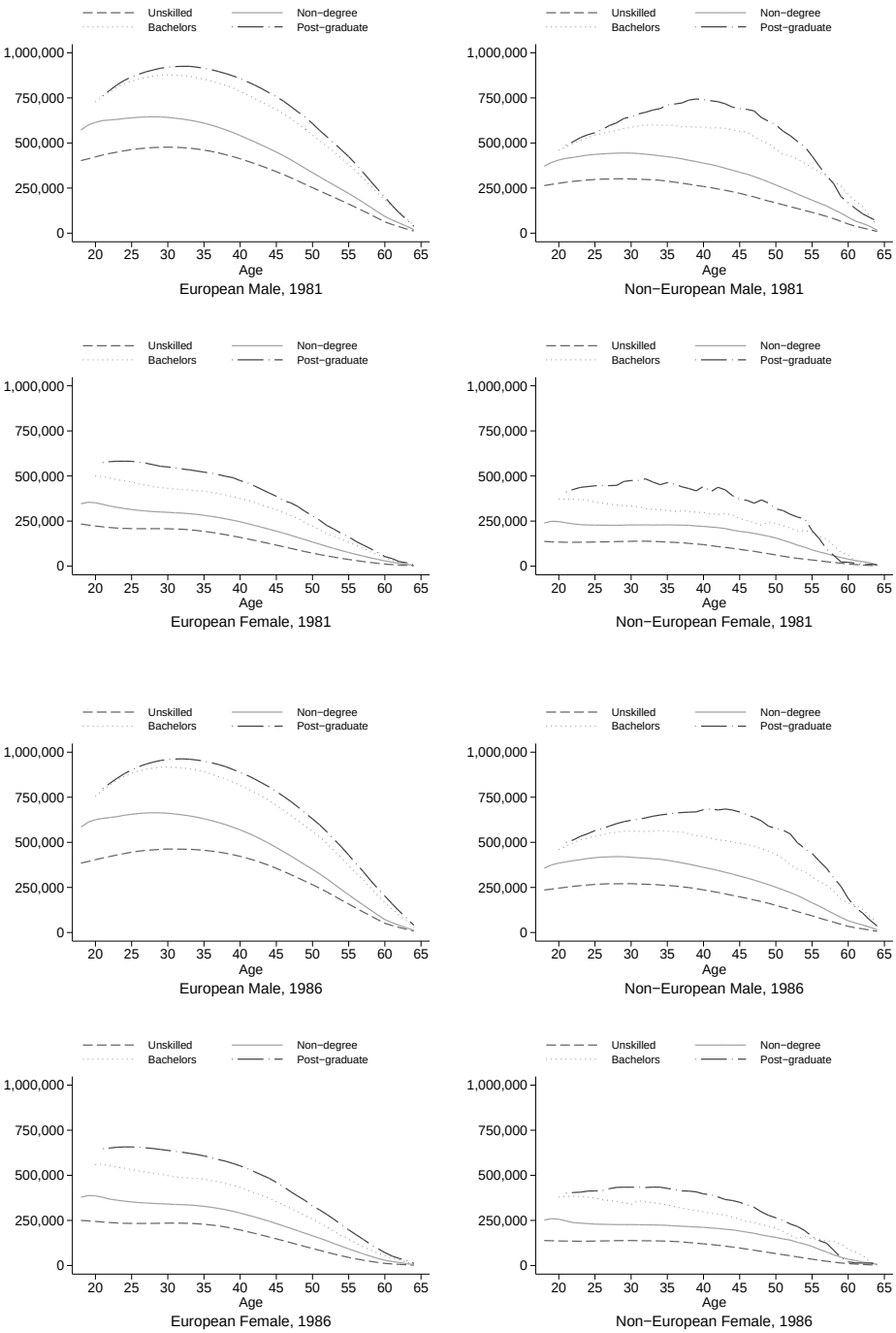
In 2001 prices, the stock of human capital was worth $521 billion in 1981, rising to $811 billion in 2001 (Table 4.6). Unskilled people, women and non-Europeans are under-represented in the human capital stock. But while there were marked increases in the shares of women and non-Europeans, the 'unskilled' share fell dramatically; the proportion of the human capital stock contributed by unskilled individuals was only 29 percent in 2001, compared with 49 percent 20 years earlier. While changes in female and unskilled groups arise from movements in the labour market, the greater share by non-Europeans in the human capital stock partly reflects the higher non-response rate to the ethnicity question.

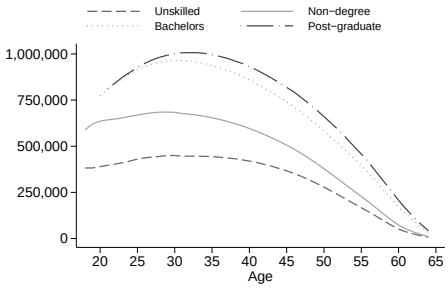
Table 4.5: Per capita lifetime labour income by ethnicity

	1981	1986	1991	1996	2001
European Male					
Unskilled	332.5	332.0	324.9	333.3	320.1
Non-degree	516.1	509.9	531.0	569.9	571.8
Bachelors	747.1	781.7	815.2	826.8	830.1
Post-graduate	762.3	775.5	800.1	830.7	824.4
Weighted average	424.9	451.7	473.0	489.5	501.9
European Female					
Unskilled	134.9	157.1	173.3	194.5	200.4
Non-degree	256.9	285.5	316.4	345.8	355.3
Bachelors	399.4	456.7	507.9	556.4	600.1
Post-graduate	436.2	519.0	586.3	671.9	743.6
Weighted average	181.0	221.7	258.8	292.5	327.9
Non-European Male					
Unskilled	250.2	222.9	202.1	202.9	197.5
Non-degree	394.3	366.6	340.8	336.3	300.8
Bachelors	544.4	517.4	498.6	474.1	461.5
Post-graduate	652.9	606.5	568.1	522.1	487.7
Weighted average	283.5	272.4	263.5	254.7	255.5
Non-European Female					
Unskilled	112.3	114.0	113.0	118.1	114.1
Non-degree	219.6	219.0	214.8	221.3	202.4
Bachelors	333.2	339.3	389.5	421.6	470.2
Post-graduate	415.4	390.7	447.2	467.6	502.7
Weighted average	131.2	141.8	154.3	162.3	177.9
All Unskilled	218.0	219.3	219.1	226.2	222.0
All Non-degree	391.4	398.6	410.5	426.5	410.9
All Bachelors	612.4	638.3	654.0	653.7	656.8
All Post-graduate	671.1	672.4	695.5	720.1	730.7
All Male	403.4	422.0	433.2	428.0	432.1
All Female	173.3	208.1	238.2	257.7	284.0
All European	303.7	337.3	365.9	390.0	413.3
All Non-European	207.0	206.5	207.6	207.4	215.1
Overall average	288.8	315.3	335.2	341.6	356.1
Change from last census (%)		9.2	6.3	1.9	4.2

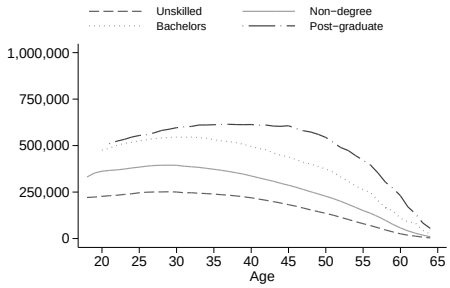
Note: See Table 3.3 (page 76).

Figure 4.1: Lifetime labour income

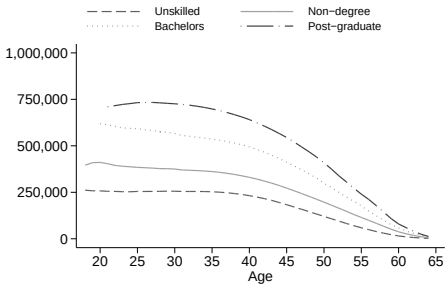




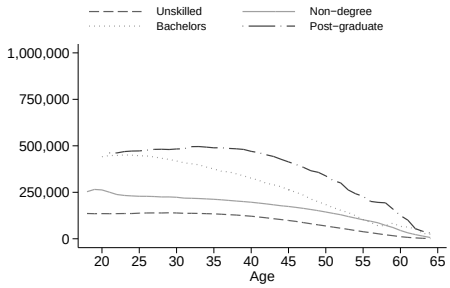
European Male, 1991



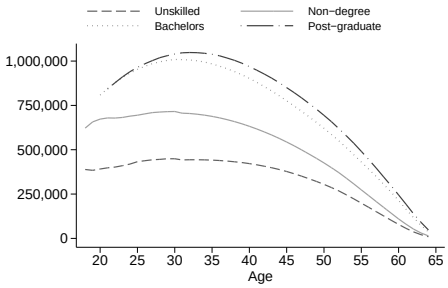
Non−European Male, 1991



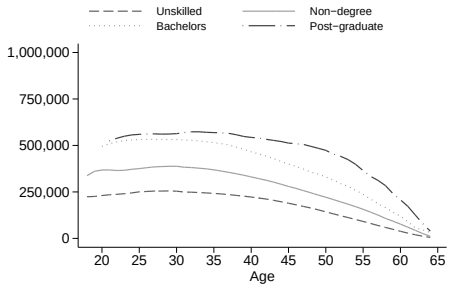
European Female, 1991



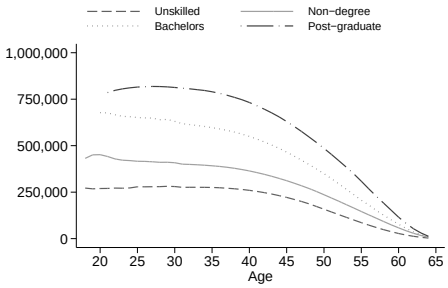
Non−European Female, 1991



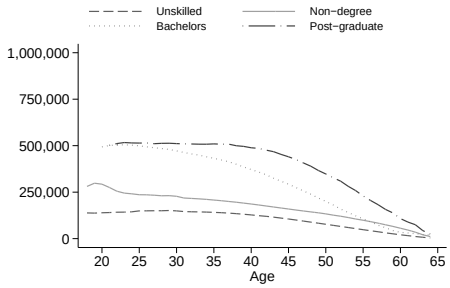
European Male, 1996



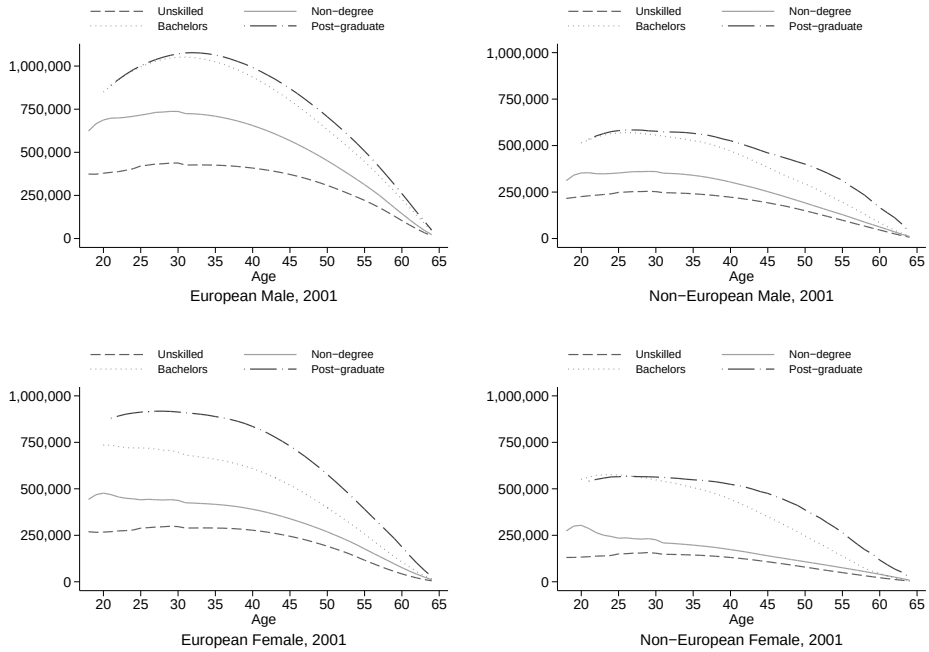
Non−European Male, 1996



European Female, 1996



Non−European Female, 1996


Unskilled
Non−degree
Bachelors
Post−graduate
1,000,000
750,000
500,000
250,000
0
20 25 30 35 40 45 50 55 60 65
Age
European Male, 2001
Non−European Male, 2001
European Female, 2001
Non−European Female, 2001

Note: In $2001

Table 4.6: Aggregate human capital stock by ethnicity

	1981	1986	1991	1996	2001
European Male					
Unskilled	146.4	122.2	108.5	125.0	105.6
Non-degree	146.0	191.8	219.0	189.7	204.7
Bachelors	26.4	32.3	39.7	50.7	58.7
Post-graduate	7.9	20.4	21.8	27.1	30.1
Sub-total	326.6	366.7	389.0	392.6	399.1
European Female					
Unskilled	67.5	72.4	71.4	80.6	69.5
Non-degree	60.6	86.4	113.0	113.2	131.9
Bachelors	7.8	11.8	18.1	29.2	45.2
Post-graduate	1.6	7.6	10.4	16.4	24.3
Sub-total	137.5	178.2	213.0	239.5	270.9
Non-European Male					
Unskilled	27.6	25.3	24.5	40.1	36.2
Non-degree	9.6	15.3	21.1	22.6	31.0
Bachelors	1.5	2.0	3.5	6.5	8.8
Post-graduate	0.4	1.3	1.8	3.4	4.3
Sub-total	39.1	44.0	50.9	72.6	80.3
Non-European Female					
Unskilled	13.1	14.3	15.3	24.5	21.6
Non-degree	4.6	7.7	12.9	16.4	24.9
Bachelors	0.5	0.9	2.3	5.5	10.8
Post-graduate	0.1	0.5	0.9	2.1	3.7
Sub-total	18.3	23.3	31.3	48.5	60.9
All Unskilled	254.5	234.3	219.6	270.1	233.0
All Non-degree	220.8	301.2	366.0	342.0	392.5
All Bachelors	36.1	47.0	63.5	92.0	123.4
All Post-graduate	10.0	29.8	34.9	49.0	62.4
All Male	365.7	410.7	439.9	465.1	479.5
All Female	155.8	201.5	244.3	288.0	331.8
All European	464.1	545.0	601.9	632.0	670.0
All Non-European	57.4	67.3	82.2	121.1	141.2
Total	521.5	612.2	684.1	753.1	811.3
Change from last census (%)		17.4	11.7	10.1	7.7

Note: See Table 3.5 (page 77).

4.4 Comparison of two sets of results

Compared with the estimates of average lifetime income in Chapter 3 (Table 3.4), my new results are around 30 percent lower, because they ignore non-market human capital. Moreover, these results do not assume constant, overstated growth rates in annual income, employment and labour-force participation.

A more salient difference is in the time trend. There was a decrease in à-la-Jorgenson-Fraumeni estimates of average lifetime income between 1981 and 1986, while according to the 'new' estimates, the strongest growth was exactly between those years. While the highest increase (8.5%) in average lifetime income estimated by the Jorgenson and Fraumeni method was during 1991-1996, the lowest inter-censual growth (1.9%) in the new results was precisely over that time. We can see from Figure 4.2 that the human capital values computed by Jorgenson and Fraumeni's method move in sympathy with the employment rate and average annual income for employed individuals, whereas the new measure is additionally influenced by labour-force participation probabilities.

Furthermore, the new estimates display larger changes in sub-populations' shares in the stock of human capital. Women's share grew from 30 percent in 1981 to 41 percent in 2001, reflecting the ever-increasing participation by women and the withdrawal by men from the labour force. This result contrasts sharply with the findings in Chapter 3, where women's share stabilised around 40 percent throughout the period. Jorgenson and Fraumeni's approach shows that the share of unskilled individuals' human capital de-

clined from 44 percent in 1981 to 34 percent in 2001. The corresponding change in the new results is far more pronounced, from 49 to 29 percent.

Not only do they exhibit sharper changes over time, the new estimates also show greater inequality in human capital across cohorts. Table 4.7 reveals that the Gini coefficient is around 0.35 for this set of estimates, much higher than the corresponding number of 0.27 for the results in Chapter 3. The disparity is accentuated when we compare the average lifetime incomes of the highest- and lowest-ranked cohorts; they differ by a factor of 40-60 in the à-la-Jorgenson-Fraumeni estimates but by up to 270-880 in the new findings.[26] The reason for this discrepancy is threefold. First, the new estimates are based on a finer breakdown of the population. Second, they allow for heterogeneity in growth rates in income, employment and survival probabilities. Most importantly, they account for labour-force participation and this variable differs tremendously from one group to another.

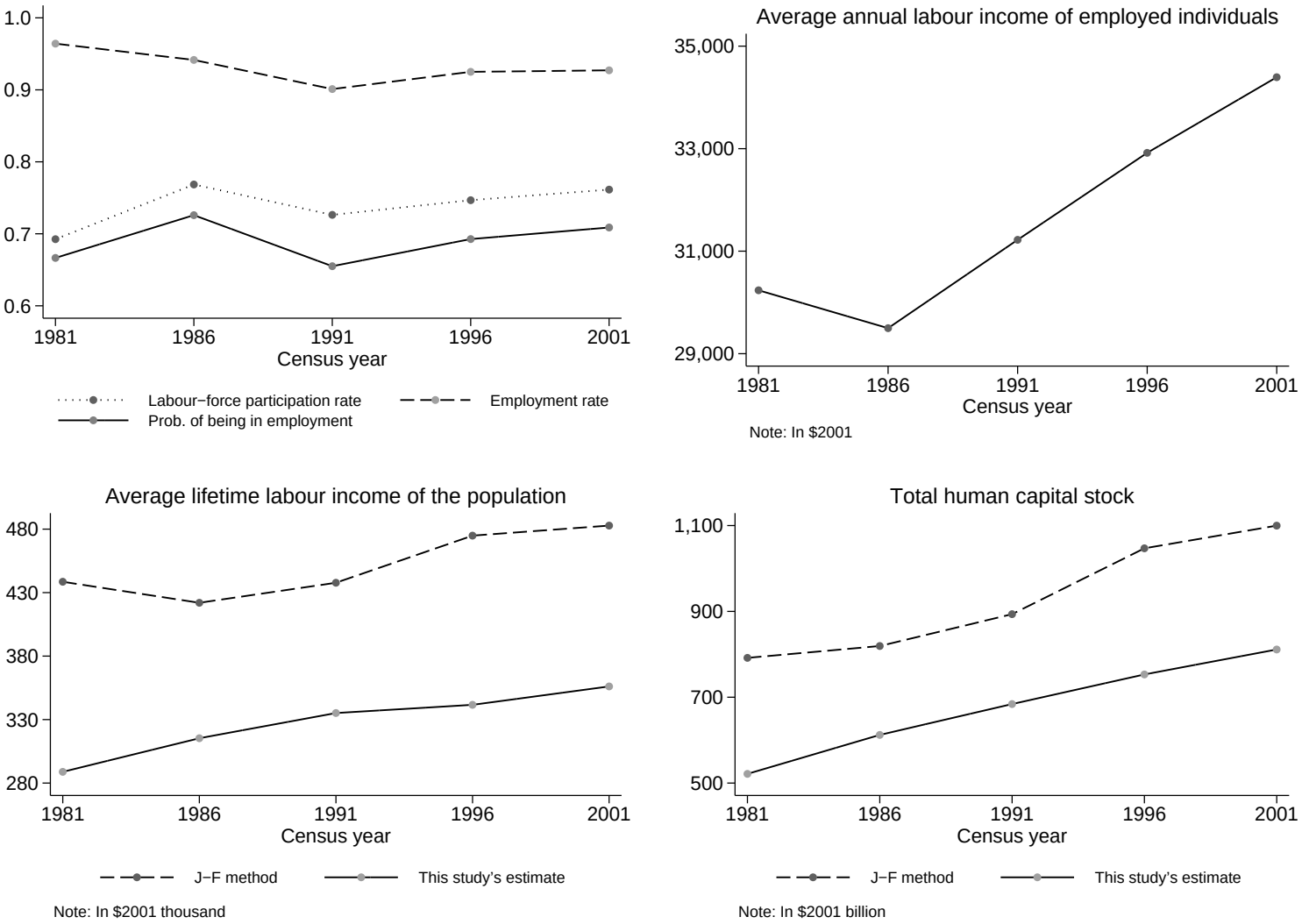
Table 4.7: Inequality in human capital across cohorts

	Max to min ratio		Gini coefficient	
Year	(a)	(b)	(a)	(b)
1981	39:1	471:1	0.26	0.38
1986	51:1	514:1	0.28	0.37
1991	55:1	879:1	0.27	0.35
1996	56:1	330:1	0.27	0.35
2001	60:1	267:1	0.27	0.35

Note: Max to min ratio compares the average lifetime labour income of the highest-ranked cohort to that of the lowest-ranked cohort. (a) Based on results from Section 3.3. (b) Based on results from Section 4.3.

[26]The estimates in Table 4.7 understate the true inequality because they ignore differences in human capital between individuals within each cohort.

Figure 4.2: Comparing two sets of estimates of human capital



Both of these sets of estimates are based on a lifetime labour income approach; to see which findings make more sense, we first need to review the labour market conditions in New Zealand during the period studied.

4.5 New Zealand labour market 1981-2001

The New Zealand economy has undergone sweeping reforms in the last two decades. In the early 1980s, the product and labour markets were characterised by a high degree of regulation, protection and price and wage setting. Wages were believed to be overvalued by reflecting relativities rather than competitive pressures. Unemployment was low, which some economists attributed to compulsory unionism, as trade unions are especially concerned with ensuring high employment for their members. But unemployment worsened; some contemporary economists blamed this on overvalued real wages, while others argued that labour market rigidities were thwarting adjustment to changing circumstances (Maloney and Savage, 1996).

Poor productivity growth and high inefficiencies in product and labour markets were among the major factors that intensified the pressure for reform, which resulted in a comprehensive economic reshuffle in 1984. The reform process can be divided into two phases: the first phase, extending until late 1990, was mainly product-market reforms, while the second phase saw more fundamental restructuring of the labour market.

Following the economic reforms, unemployment began to soar; it increased from 3.8 percent in December 1985 to a peak of 11 percent in March 1992. The rising unemployment in these years was closely related to the

contraction in employment level which, according to Silverstone and Daldy (1993), was almost unique to New Zealand, among OECD countries. Employment declined not because of excess of quits, layoffs and redundancies over new hires and recalls but because of the positive net flows from employment to out of the labour force, probably due to early retirements, non-renewals of contracts, increased retraining and discouragement (Silverstone and Daldy, 1993). This evidence concurs with Dalziel and Lattimore (1999) who point out that the decline in employment was largely caused by the falling aggregate demand, rising productivity and large-scale redundancies as a result of the economic restructuring. Maloney and Savage (1996) explain that at least temporarily lower employment was expected in view of increased competition in product markets, a higher wage floor, and geographic and skill mismatches between dislocated workers and emerging job vacancies during the reform.

The second phase of the reform started with the introduction of the Employment Contracts Act (ECA) in May 1991. The ECA was intended to "promote an efficient labour market," based on the argument that greater labour market flexibility enhances economic growth, productivity and employment. This Act saw a shift away from the existing centralised bargaining system with occupational awards and blanket coverage towards a highly decentralised, enterprise-level bargaining system. Employment then picked up, but it was unclear whether this positive outcome was due to the product-market reforms in the first phase, the worldwide economic recovery, a lower wage floor, or simply a rebound after a long recession. Maloney and Savage find that some 22 percent employment growth between June 1991 and December 1993 was attributable to the ECA. The ECA may have reduced

the influence of unions, thereby raising the demand for labour and cutting unemployment.

Male labour-force participation has been declining but this drop has been more than offset by the higher female participation. According to Silverstone and Daldy, this outcome is due both to the expansion in community, social sector employment where women dominate, and to the contraction in the traditionally male-dominated manufacturing and construction sectors. The greater aggregate participation could partly be influenced by the social welfare system. Previously, generous income support (domestic-purposes benefit), loose entitlements to this benefit and high effective marginal tax rates for the beneficiaries meant that it was preferable for non-working people to be out of the labour force than on the dole. These disincentives have been largely reduced following the introduction of an "Economic and Social Initiative" in December 1990 which lowered benefit rates, tightened eligibility criteria and initiated a review of the targeting of social assistance in general. However, there is evidence that labour supply increased more because of the economic recovery in 1993-1994 than because of the tightened eligibility under the 1990 social welfare reform (Maloney and Savage, 1996).

4.6 Discussion

From Table 3.1, university graduates have increased both in number and as a proportion of the population. Any education-based measure would suggest that New Zealand's human capital has grown rapidly. But the two sets of results reported in Sections 3.3 and 4.3 are not education-oriented; they do

not evaluate human capital by counting how much education people have accumulated. Being based on a labour income approach, these estimates assume that labour income reflect marginal productivity of labour and that labour productivity is a proxy for human capital.

In reality, wages and productivity do not always move in tandem. Pre-reform real wages were overvalued because they were traditionally set on the basis of occupational relativities rather than on productivity. The presence of effective legislated wage floors, which can be as high as 53 percent of average earnings, also indicates that wages may reflect equity considerations rather than market conditions. Besides, in an attempt to fight inflation, a price and wage freeze was introduced in June 1982. Real wages then declined for the next three years and this was part of the reason why real earnings in 1986 were so low. Real wages continued to trend downwards until 1990 although this trend has later reversed. Some authors, including Grimes (1981) and the Reserve Bank of New Zealand (1982), assert that real-wage overvaluation before the reform was a major cause for rising unemployment. Despite rising productivity, real wages fell in the first phase of the reform (1984-1990) to ease the pressure on high unemployment at that time (Dalziel and Lattimore, 1999).

The fluctuations in real wages in the first phase of the reform are well reflected in the à-la-Jorgenson-Fraumeni estimates of human capital. However, both macro and micro evidence suggests that labour productivity has experienced steady growth in the last two decades.[27] Those data show no

[27]See Black et al. (2003); Diewert and Lawrence (1999); Law and McLellan (2005); Maloney and Savage (1996).

inter-censual decrease in labour productivity, even when real wages were falling. If labour productivity is a proxy for human capital, then the estimates of human capital obtained in Chapter 3 are inconsistent with reality. Indeed, it is hard to justify why human capital declined in a period (1981-1986) when educational attainment and labour-force participation increased substantially. The new measure of human capital is more pro-cyclical. It grew steadily from census to census, well in line with the trends in participation, employment, real wages and labour productivity.

My measure of human capital is strictly confined to economic production. My model maintains that the human capital that is not used in economic activities is useless. The method places less weight on the contribution of the less participating groups (eg. women, non-Europeans and unskilled individuals). Be it a choice or a risk, non-participation means people's knowledge and skills are wasted through idleness and so their *effective* human capital, economically speaking, is zero. My estimates are significantly lower than à-la-Jorgenson-Fraumeni results, but I argue that Jorgenson and Fraumeni's model exaggerates human capital by unduly accounting for non-market activities.[28]

My results imply that the population size does not matter much to the total stock of human capital; what is more important is people's participation in economic activity. Accordingly, getting more migrants will not lift the stock of human capital if these migrants end up being out of employment. The human capital stock can still be enhanced based on the same population

[28] Jorgenson and Fraumeni (1989, 1992) also impute the time that workers spend outside work (and 'maintenance' activities), the value of non-workers is raised accordingly.

stock by increasing the participation rate, other things being equal. Likewise, educating people is not sufficient to boost the country's human capital; it is necessary that those people be employed so that the knowledge and skills that they have acquired are turned into productive capital rather than being squandered on unemployment and non-participation.

Nevertheless, my estimates are still subject to a well known problem concerning a general lifetime income approach, namely omitted variables bias. This problem arises because ethnicity, gender, education and age are not sufficient to explain variations in earnings. Several important factors, including ability, family background, quality of schooling and work experience, have been left out of the model. I would argue that this bias matters more to estimates for individuals than to population aggregate results.

4.7 Human capital and physical capital compared

Some comparisons between human and physical capital stocks are reported in Table 4.8. Similar to the case of Australia (Wei, 2003), the value of New Zealand's working human capital stock is more than double that of the physical capital stock and this ratio trends upwards over time.

However, this comparison is rather naïve, since physical capital is measured in terms of the cost of production, while human capital in this study is measured by its yield. Even though the cost and the yield approaches are theoretically equivalent, their results do not always agree in reality. Be-

Table 4.8: Human and physical capital stocks

	1981	1986	1991	1996	2001
Human capital	207.2	364.9	585.0	688.0	811.3
Physical capital*		169.4	214.8	264.6	309.0
Human: Physical		2.2	2.7	2.6	2.6

Note: Physical capital estimates are obtained from PC-INFOS Series SNCA.S5NK90ZZ. *Statistics not publicly available for 1981. The figure for 1985/1986 is not publicly available so the corresponding value for 1986/1987 is used here. All capital stock values are in current billion dollars.

sides, the human capital estimates are 'gross' in that maintenance costs are not deducted from labour incomes, whereas estimates of physical capital are net.[29]

On the contrary, my measure of human capital is quite conservative in the sense that it excludes non-market activities, which have been found by other studies to be of significance. When non-work hours are evaluated at the after-tax wage rate, the stock of human capital exceeds that of physical capital by over 10 times for the US (Jorgenson and Fraumeni, 1989) and by 6-10 times for Sweden (Ahlroth et al., 1997). But Jorgenson and Fraumeni's method of imputing non-market time has attracted considerable criticism. Hence, how to appropriately take account of non-economic human capital is still a controversial matter.

[29] As discussed in Section 2.3.2, whether or not human capital values should be net of maintenance expenses remains unsettled.

Chapter 5

Decomposing changes in human capital

5.1 Models

The stock of human capital is composed of the human capital of all ethnic-gender-education-age cohorts in the population. However, ethnicity is subjective; people's perception about their ethnicity can change over time and across contexts (Statistics New Zealand, 2004). More and more people have also skipped the question about ethnicity in the census. Thus, I will omit this variable from the decomposition. The current stock of human capital can be expressed as:

$$\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64} N^{y}_{s,e,a} H^{y}_{s,e,a} \tag{5.1}$$

and the corresponding stock in a past year:

$$\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64} N_{s,e,a}^{y-t} H_{s,e,a}^{y-t} \tag{5.2}$$

where:

$s =$ gender (1=male, 2=female);

$e =$ education level (1=unskilled, 2=non-degree, 3=Bachelors, 4=post-graduate);

$a =$ age;

$N =$ size of cohort;

$H =$ average per capita human capital;

$y =$ current year;

$y - t =$ past year.

Change in the stock between year $y - t$ and year y is:

$$\begin{aligned}
&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64} N_{s,e,a}^{y} H_{s,e,a}^{y} - \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64} N_{s,e,a}^{y-t} H_{s,e,a}^{y-t} \\
=&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{17+t} N_{s,e,a}^{y} H_{s,e,a}^{y} + \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18+t}^{64} N_{s,e,a}^{y} H_{s,e,a}^{y} \\
&- \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N_{s,e,a}^{y-t} H_{s,e,a}^{y-t} - \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=65-t}^{64} N_{s,e,a}^{y-t} H_{s,e,a}^{y-t}
\end{aligned} \tag{5.3}$$

Note that:

$$\sum_{a=18+t}^{64} N_{s,e,a}^{y} = \sum_{a=18}^{64-t} N_{s,e,a+t}^{y} = \sum_{a=18}^{64-t} (N_{s,e,a}^{y-t} + N_{s,e,a+t}^{y} - N_{s,e,a}^{y-t}) \tag{5.4}$$

Considering the second and third terms of (5.3):

$$
\begin{aligned}
&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18+t}^{64} N^{y}_{s,e,a}H^{y}_{s,e,a} - \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}H^{y-t}_{s,e,a} \\
=&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} (N^{y-t}_{s,e,a} + N^{y}_{s,e,a+t} - N^{y-t}_{s,e,a})H^{y}_{s,e,a+t} - \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}H^{y}_{s,e,a} \\
&+\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}H^{y}_{s,e,a} - \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}H^{y-t}_{s,e,a} \\
=&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}(H^{y}_{s,e,a+t} - H^{y}_{s,e,a}) + \sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} N^{y-t}_{s,e,a}(H^{y}_{s,e,a} - H^{y-t}_{s,e,a}) \\
&+\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t} (N^{y}_{s,e,a+t} - N^{y-t}_{s,e,a})H^{y}_{s,e,a+t}
\end{aligned}
\tag{5.5}
$$

$H^{y}_{s,e,a+t} - H^{y}_{s,e,a}$ reflects depreciation in human capital. As people get older they have a shorter period to be of economic value to the society, their human capital thus 'depreciates.' Depreciation can, however, be positive, if the effect of experience on one's earnings prospects is large enough to outweigh the effect of aging.

The difference $H^{y}_{s,e,a} - H^{y-t}_{s,e,a}$ is termed revaluation of human capital. Revaluation refers to the fact that certain cohorts have earnings, labour-force participation, employment and mortality rates that are different from their counterparts in the past year, thus the value of their human capital would be different. Since mortality rates change little, revaluation of human capital mainly captures changes in labour market conditions.

$N^{y}_{s,e,a+t}$ differs from $N^{y-t}_{s,e,a}$ because between year $y-t$ and year y people immigrated, emigrated, died, or improved their qualification. So,

$$\begin{aligned}
&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t}(N^{y}_{s,e,a+t}-N^{y-t}_{s,e,a})\\
=&\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t}(I^{y-t,y}_{s,e,a}-E^{y-t,y}_{s,e,a}-D^{y-t,y}_{s,e,a})\\
&+\sum_{s=1}^{2}\sum_{a=18}^{64-t}\{-(J^{y-t,y}_{s,a,(e_1,e_2)}+J^{y-t,y}_{s,a,(e_1,e_3)})+(J^{y-t,y}_{s,a,(e_1,e_2)}-J^{y-t,y}_{s,a,(e_2,e_3)})\\
&\qquad+(J^{y-t,y}_{s,a,(e_1,e_3)}+J^{y-t,y}_{s,a,(e_2,e_3)}-J^{y-t,y}_{s,a,(e_3,e_4)})+J^{y-t,y}_{s,a,(e_3,e_4)}\}
\end{aligned} \tag{5.6}$$

where $I^{y-t,y}_{s,e,a}$, $E^{y-t,y}_{s,e,a}$ and $D^{y-t,y}_{s,e,a}$ are respectively the numbers of people aged a in year $y-t$ who have immigrated, emigrated or died and $J^{y-t,y}_{s,a,(e_i,e_j)}$ the number of people who have upgraded their education profile before year y.

Given (5.4)-(5.6), (5.3) can be rewritten as:

$$\begin{aligned}
&\sum_{s=1}^{2}\sum_{e=1}^{4}(\sum_{a=18}^{17+t}N^{y}_{s,e,a}H^{y}_{s,e,a}-\sum_{a=65-t}^{64}N^{y-t}_{s,e,a}H^{y-t}_{s,e,a})\\
&+\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t}N^{y-t}_{s,e,a}(H^{y}_{s,e,a+t}-H^{y}_{s,e,a})+\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t}N^{y-t}_{s,e,a}(H^{y}_{s,e,a}-H^{y-t}_{s,e,a})\\
&+\sum_{s=1}^{2}\sum_{e=1}^{4}\sum_{a=18}^{64-t}(I^{y-t,y}_{s,e,a}-E^{y-t,y}_{s,e,a}-D^{y-t,y}_{s,e,a})H^{y}_{s,e,a+t}\\
&+\sum_{s=1}^{2}\sum_{a=18}^{64-t}\{-(J^{y-t,y}_{s,a,(e_1,e_2)}+J^{y-t,y}_{s,a,(e_1,e_3)})H^{y}_{s,e_1,a+t}+(J^{y-t,y}_{s,a,(e_1,e_2)}-J^{y-t,y}_{s,a,(e_2,e_3)})H^{y}_{s,e_2,a+t}\\
&\qquad+(J^{y-t,y}_{s,a,(e_1,e_3)}+J^{y-t,y}_{s,a,(e_2,e_3)}-J^{y-t,y}_{s,a,(e_3,e_4)})H^{y}_{s,e_3,a+t}+J^{y-t,y}_{s,a,(e_3,e_4)}H^{y}_{s,e_4,a+t}\}
\end{aligned} \tag{5.7}$$

That is, changes in the stock of human capital can be decomposed into:

+ addition of young workers

− retirement of old workers

and for other ages:

+ appreciation/depreciation in human capital

+ revaluation of human capital

+ immigration

− emigration

− death

+ investment in education

5.2 Data

I assume that those who were enrolled for a qualification e_j in year $y-5$ are already in education cohort e_j in year y. Data on death tolls are obtained from *New Zealand Life Tables*.

Census questionnaires do not explicitly ask if a person is an immigrant, while emigrants are unidentifiable because they are no longer in the country. Given this deficiency, I assume that a resident is a new migrant if he was not usually in New Zealand in the last census year.[30] Migrants, according to this definition, are not necessarily overseas-born; they may just be New Zealanders who have recently returned after living abroad for more than

[30]Based on, for example, question 7 in Census 2001: "Where did you usually live 5 years ago on 6 March 1996?". The phrase "usually live" precludes the possibility of identifying people who are temporarily overseas on a census day as migrants in the next census.

five years. This should not be an issue, because I am interested more in population inflows and outflows than in 'pure' migration. The number of emigrants is calculated as the balance of all other demographic changes, based on equation (5.6).

5.3 Results

The biggest contribution to changes in the human capital stock is the entrance of young people into the work force (Table 5.1). However, this effect has been declining. The addition of young workers raised the human capital stock by 21 percent between 1981 and 1986, but between 1996 and 2001 this impact dropped to only 14 percent.

Depreciation, on the contrary, represents a major cause for contraction in human capital. Even though human capital diminishes as one ages, it often appreciates for ages 23-31 (the youngest age cohorts in the previous census year, see Figure 5.1). This is because while aging shortens a person's economic life, for the youngest ages the value of experience and education is more than enough to offset the negative effect that aging has on their human capital.

The stock of human capital depreciates by 9.1-9.8% between two consecutive census years. This effect has weakened, implying that gains due to experience have become relatively more important to human capital formation than losses caused by aging. The role of education can be inferred seeing that appreciation is much higher for university graduates than for non-graduates. Like lifetime income, depreciation displays flatter patterns

Table 5.1: Decomposition of percentage changes in stocks of human capital

	1981-86	1986-91	1991-96	1996-01	1981-01
Male					
Addition	13.1	11.4	9.2	7.9	51.3
Retirement	-0.5	-0.4	-0.4	-0.4	-11.0
Depreciation	-5.8	-5.6	-5.2	-5.0	-17.4
Revaluation	-0.8	-0.4	0.9	-0.7	-3.7
Edu. investment	0.6	0.6	1.0	1.3	0.7
Death	-0.7	-0.7	-0.7	-0.6	-1.9
Immigration	10.3	5.4	9.5	6.1	
Emigration	-7.4	-5.6	-10.7	-6.7	
Sub-total	8.6	4.8	3.7	1.9	21.8
Female					
Addition	7.8	7.3	6.5	6.0	37.9
Retirement	-0.1	-0.1	-0.1	-0.2	-3.2
Depreciation	-4.1	-3.9	-4.0	-4.1	-11.8
Revaluation	3.7	2.7	2.6	1.7	6.6
Edu. investment	0.3	0.5	0.9	1.3	0.4
Death	-0.2	-0.2	-0.2	-0.2	-0.6
Immigration	3.8	3.3	5.5	5.3	
Emigration	-2.5	-2.7	-4.8	-4.0	
Sub-total	8.8	7.0	6.4	5.8	33.8
Total	17.4	11.7	10.1	7.7	55.6

Note: Based on estimates of human capital stocks in Table 4.6 (page 94). Individual effects of immigration and emigration for 1981-2001 are not determinable from census data.

for women and for non-graduates. However, depreciation accelerates faster with age for degree holders just because they have more human capital to start with. As Figure 5.2 (page 115) shows, human capital depreciates at similar rates across education levels.

The capital embodied in people is valued differently across time. This 'revaluation' effect has been positive, which reflect the favourable changes in labour supply, employment and earnings. According to Figures 5.3 and 5.4,

inter-censual changes in human capital estimates reach up to 90 percent in some cases. Absolute gains are greatest for university-educated women, but no clear patterns prevail for men. Revaluation can be negative for certain groups. Not surprisingly, most vulnerable are the very old or very young unskilled individuals, as wages and employment for these people fall faster in downturns and grow more slowly in boom times. This evidence clearly refutes the assumption made by Jorgenson and Fraumeni (1992) of equal growth rates across ages and education levels.

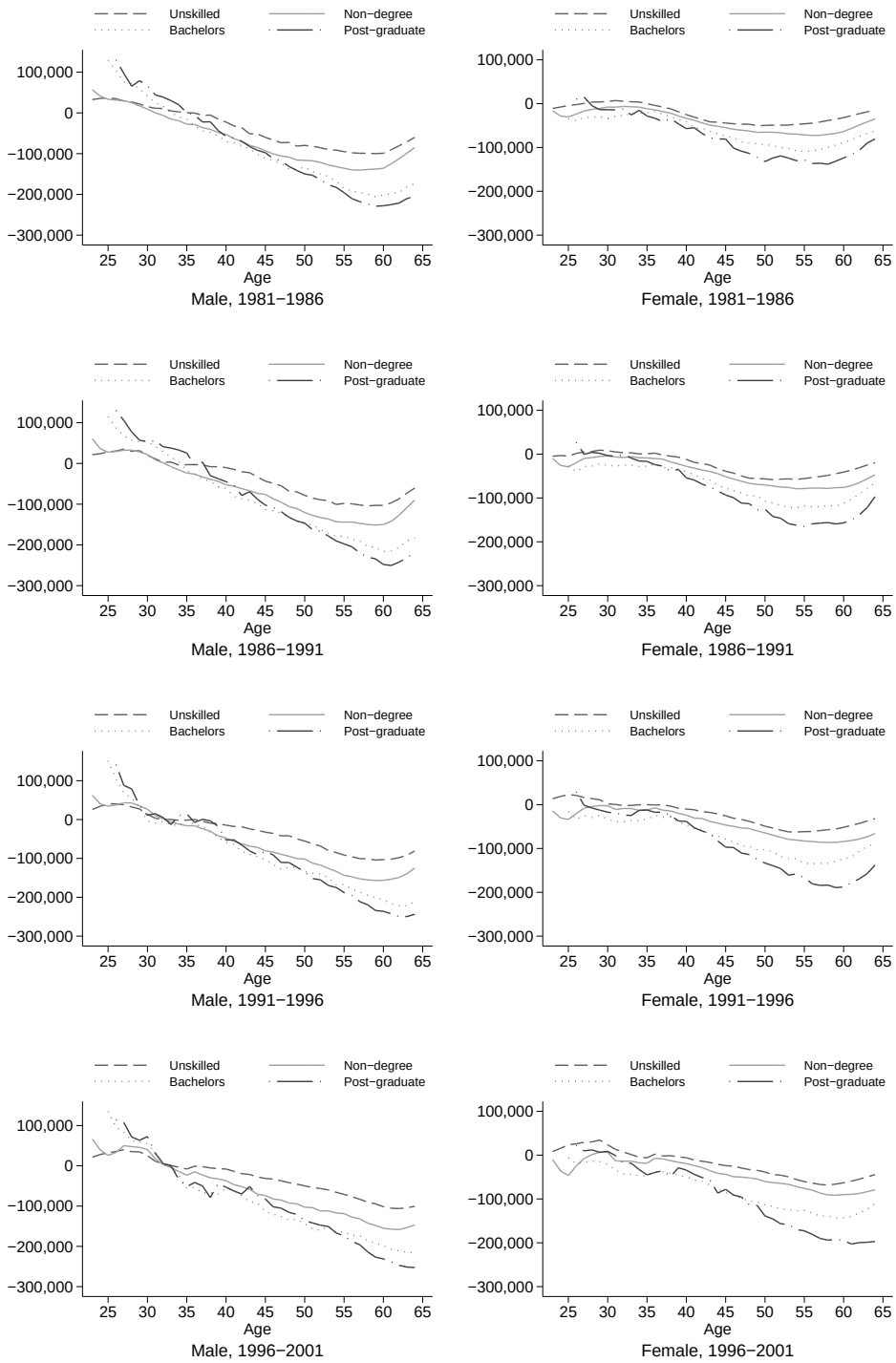
The effects of retirement and mortality have been fairly stable; altogether they reduce the stock of human capital by 1.4 percent every five years. Investment in education represents a small, yet growing, determinant of growth. This factor accounts for a growth of 2.6 percent in human capital between 1996 and 2001, reflecting a healthy increase from 0.9 percent for the period 1981-1986.

New Zealand's human capital has benefited from migration. The effect of migration peaked at 4.2 percent (1981-1986), when immigrants added 14.1 percent to the country's stock of human capital but the departure of local residents lowered it by 9.9 percent. A small 'brain drain' was recorded between 1991 and 1996, as the gain from immigration fell short of the loss from emigration by 0.5 percent. Migration components can not be determined for 1981-2001, since the two years are not consecutive census years. However, the net impact of migration can still be calculated as the balance of all other effects. For example, the changes due to immigration and emigration can be 19.3% and 11% or 25% and 16.7% or some other combination, but their net

effect is always 8.3%. That is, of the 56 percent growth in the stock of human capital between 1981 and 2001, over 8 percent was caused by migration.

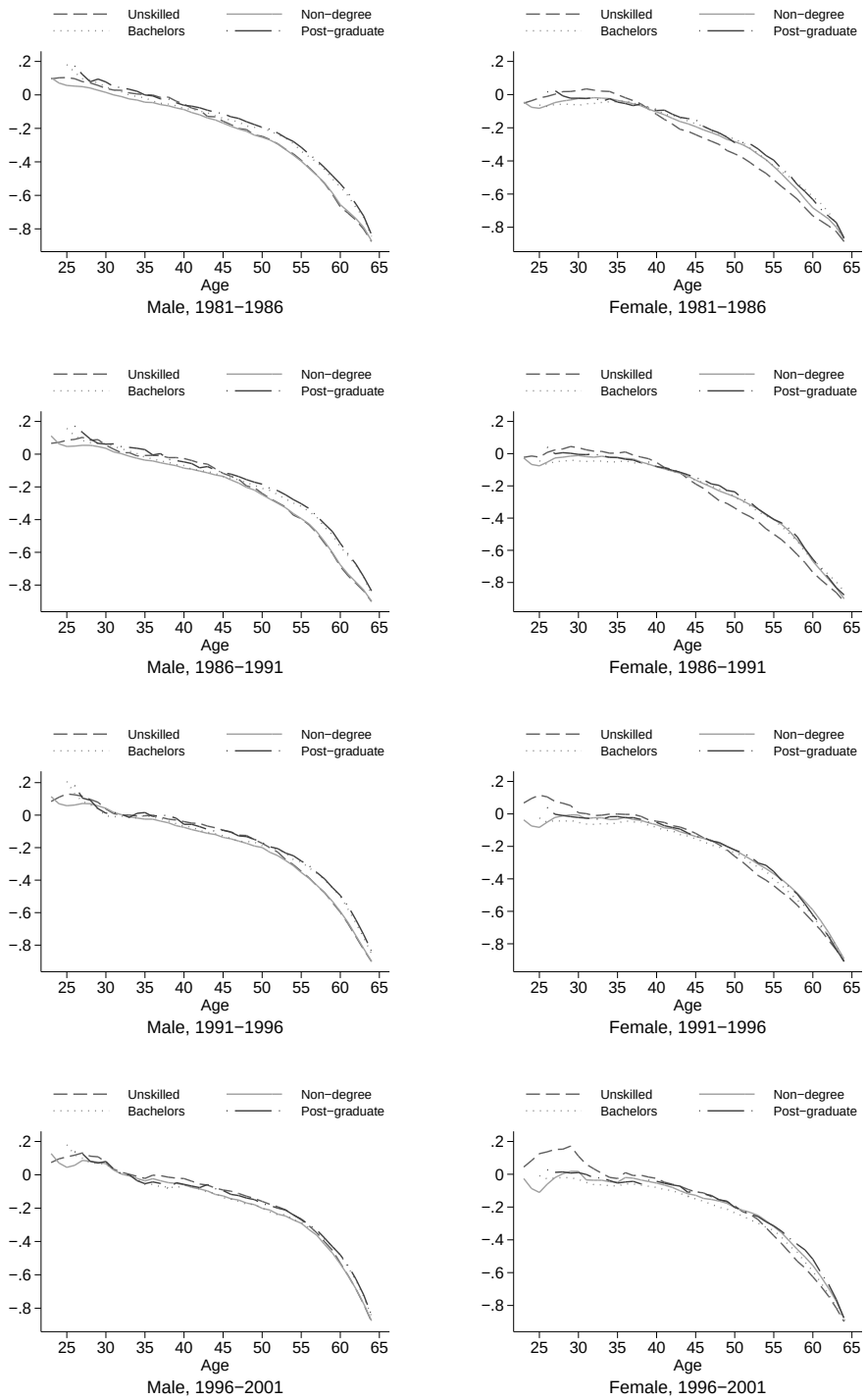
Since men make up a larger share of the human capital stock, the individual effects they have on changes in stocks are greater. The only factor in which women's influence dominates is revaluation. Women's participation in the labour force has risen enormously, making their market human capital more highly valued. Therefore, despite their under-representation in the stock of human capital, women have contributed more than men to overall changes in stocks. Women also account for most of the gain in human capital that results from migration. While the net effect of migration is often negative for men, the human capital that female migrants have brought to New Zealand has always outweighed the loss due to emigrating women.

Figure 5.1: Depreciation in human capital



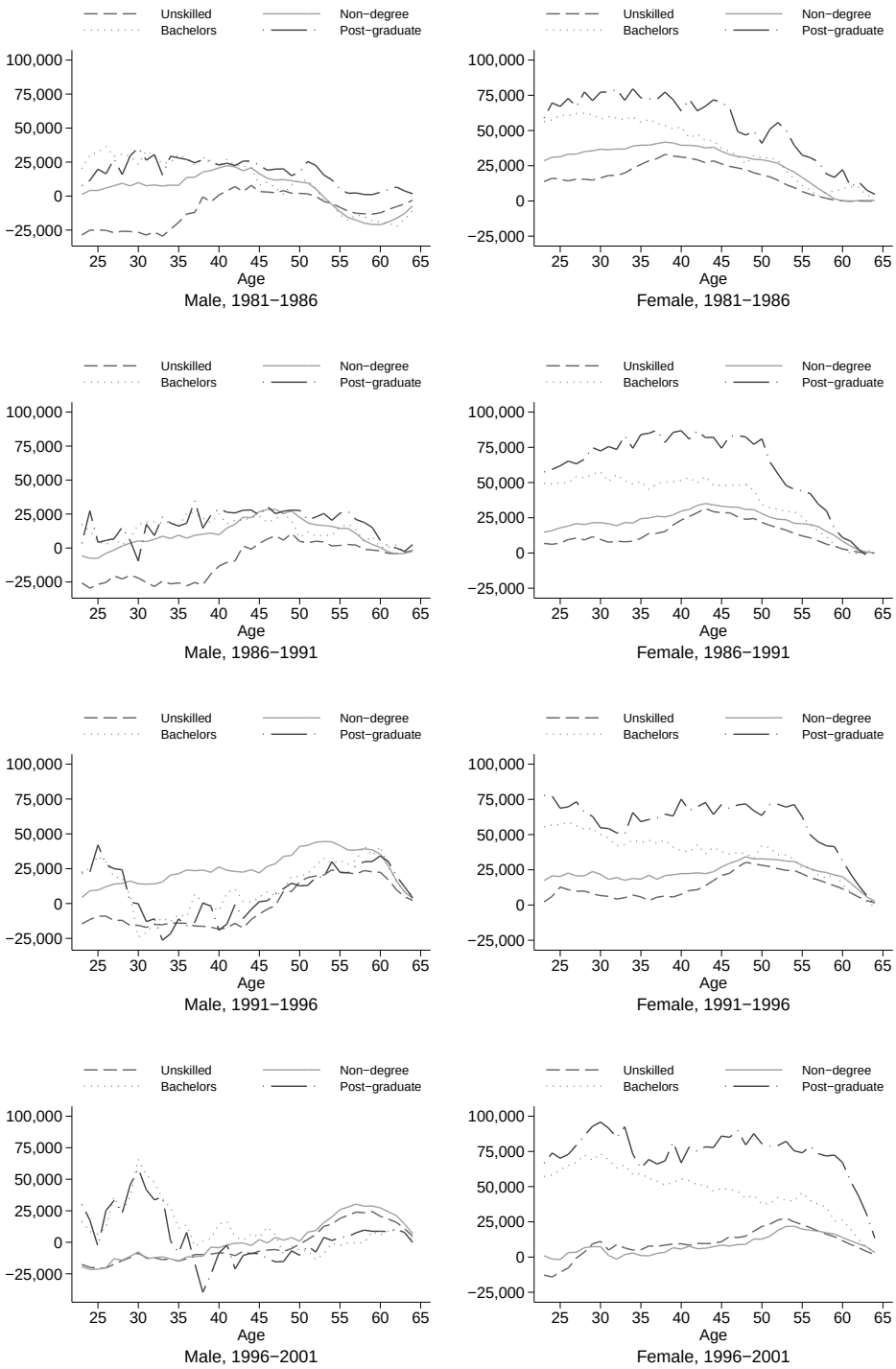
Note: In $2001. Age is as at the ending year of each period.

Figure 5.2: Rates of depreciation in human capital



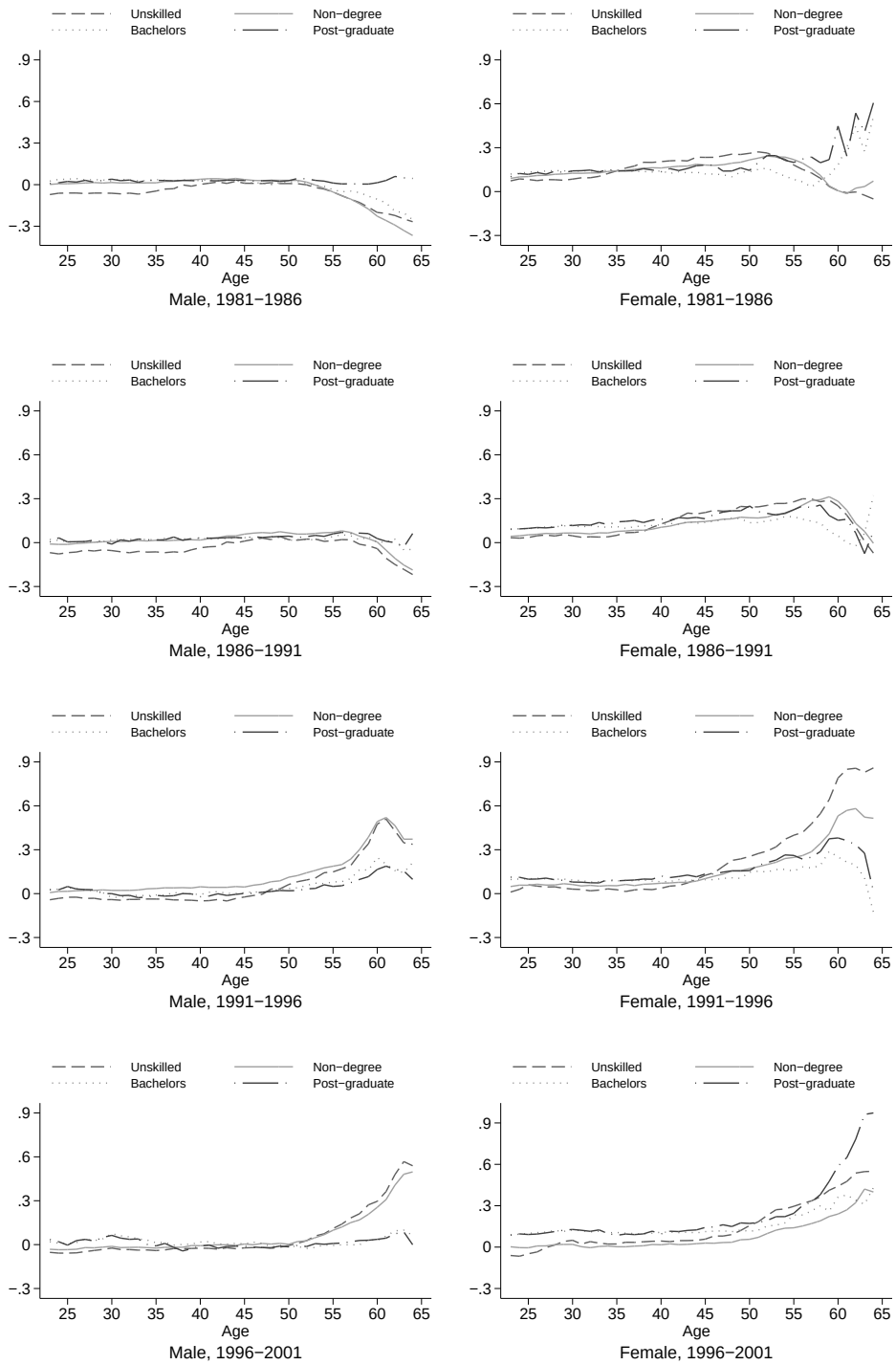
Note: Age is as at the ending year of each period.

Figure 5.3: Revaluation of human capital



Note: In $2001. Age is as at the ending year of each period.

Figure 5.4: Rates of revaluation of human capital



Note: Age is as at the ending year of each period.

Chapter 6

Human capital as a latent variable

6.1 Models

In Chapter 4, human capital is defined as lifetime labour income based on ethnicity, gender, education and age. One might argue that possible factors that affect human capital extend well beyond those variables. This chapter draws on micro data to explore other determinants. Unlike the existing literature which uses observable indicators as proxies for the unobservable human capital, this chapter characterises human capital as a multidimensional latent variable that is influenced by and reflected in many variables. To model this concept, I use a Partial Least Squares (PLS) approach.

PLS, developed by Wold (1975), is a distribution-free least squares estimation technique which models the relationship between multiple response variables and multiple explanatory variables. PLS seeks to identify the un-

derlying factors that best represent the response variables. Not only can PLS handle multiple dependent variables, it can also deal better than traditional regression methods with such problems as multicollinearity, noise, missing data and small sample size. Originally designed for econometrics, PLS has gained popularity in chemistry, information systems, medicine and psychology, while its application in economics remains limited.

A PLS model has two parts: the *inner model* and the *outer model*.[31] The inner model specifies the relationship between *latent*, or unobservable, variables ξ's:

$$\xi_j = \beta_{j0} + \sum_i \beta_{ji}\xi_i + \nu_j \tag{6.1}$$

subject to predictor specification:

$$E(\nu_j|\xi_j, \xi_i) = 0 \tag{6.2}$$

which implies zero correlation between residuals and explanatory latent variables:

$$r(\nu_j, \xi_i) = 0 \tag{6.3}$$

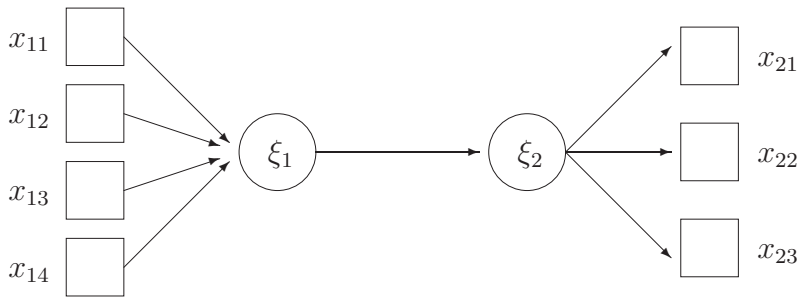
A latent variable is exogenous if it is not 'caused' by another latent variable (ξ_1 in Figure 6.1), otherwise it is endogenous (ξ_2).

The outer model describes the relationship between a latent variable and its observed, or *manifest*, variables:

$$x_{jh} = \pi_{jh0} + \pi_{jh}\xi_j + \epsilon_{jh} \tag{6.4}$$

[31] A glossary of PLS terms is provided on page 143. Comprehensive descriptions of the PLS method can be found in Wold (1982, 1985).

Figure 6.1: A general Partial Least Squares model



subject to:

$$E(\epsilon_{jh}|\xi_j) = 0 \tag{6.5}$$

where x_{jh} is the hth manifest variable of ξ_j. Manifest variables form blocks, each block being associated with one latent variable. It follows from (6.5) that within each block no correlation exists between residuals and the latent variable:

$$r(\epsilon_{jh}, \xi_j) = 0 \tag{6.6}$$

By assumption, residuals of one block are correlated with neither the latent variable nor residuals from another block:

$$r(\epsilon_{jh}, \xi_i) = 0 \tag{6.7a}$$

$$r(\epsilon_{jh}, \epsilon_{ik}) = 0 \tag{6.7b}$$

Given (6.3), (6.6) and (6.7a), residuals from the inner model and the outer model are also uncorrelated:

$$r(\epsilon_{jh}, \nu_j) = 0 \tag{6.8}$$

The 'intercepts' β_{j0} in equation (6.1) and π_{jh0} in (6.4) are termed *locations*, while the 'slopes' are respectively called *path coefficients* and *loadings*. The outer model can be specified in two modes. In *mode A*, each manifest variable 'reflects' its latent variable:

$$x_{jh} = \omega_{jh}\xi_j + \delta_{jh} \tag{6.9}$$

whereas in *mode B* the latent variable is 'formed' by its manifest variables:

$$\xi_j = \sum_h (\omega_{jh}x_{jh}) + \delta_j \tag{6.10}$$

Mode C refers to the case in which both mode A and mode B are used. In Figure 6.1, mode A represents the relationship between ξ_2 and x_2's, while the relationship between ξ_1 and x_1's is an example of mode B.

The PLS algorithm proceeds in three steps. The first step estimates latent variables. Since neither the loadings nor the latent variables are known, standardisation is necessary. Generally, all latent variables are standardised to unit variance. Using iterative Ordinary Least Squares (OLS) regressions, each latent variable is calculated as a linear combination of its manifest variables such that it does not only achieve maximal correlations with its manifest variables but is also related with other latent variables according to the inner model. The computed latent variables are then plugged into the inner and outer equations to derive their parameters. Loadings in mode A are estimated using simple OLS regressions in which each manifest variable is 'explained' by its latent variable. By contrast, weights in mode B are

based on multiple OLS regressions in which each latent variable is regressed on its manifest variables. Path coefficients of the inner model are similarly obtainable by OLS. Locations are estimated in the final step.[32]

The PLS method requires neither normal distribution nor large sample size. However, as a limited-information approach, PLS estimates are biased and inconsistent. Yet Wold (1982) showed that PLS estimates are asymptotically consistent and *consistent at large*. That is, consistency grows with sample size and as the number of manifest variables per latent variable increases. Moreover, since distributional properties of estimates are unknown, standard errors have to be calculated via bootstrap or jackknife.

According to Wold (1982), a model with one latent variable estimated by mode A is equivalent to the first principal component. In a two-latent-variable model in which both blocks are estimated by mode B, the path coefficient coincides with the first canonical correlation. When the model has one endogenous latent variable and each latent variable has only one manifest variable, PLS reduces to OLS.[33]

6.2 Data

Data for this chapter come from the International Adult Literacy Survey (IALS). The IALS was the first internationally comparative study of literacy skills. Even though the focus is on literacy, rich data on employment, income, earnings and many other socio-economic variables were also obtained.

[32]When manifest variables are centred (by subtracting their means), locations are zero.

[33]In that case, OLS and PLS produce the same 'beta' coefficients and R^2's but different standard errors because they are calculated via a resampling procedure in PLS.

The IALS applies a standardised questionnaire across countries and collects information on various forms of skills. Therefore, it is a first-choice data set for studying human capital across countries.

The first two rounds of the IALS were conducted in 1994-1996 and covered 13 OECD countries.[34] In each country, the survey drew on a probability sample that represents the civilian, non-institutionalised population aged 16-65. However, results derived from the IALS are not necessarily representative for all variables, as illustrated by the case of New Zealand below.

Table 6.1: Comparing data from the 1996 IALS and the 1996 Census

	IALS	Census
Population aged 18-64	1,328,620	2,204,634
Average age	37.5	38.3
Shares of population:		
European	.79	.74
Male	.52	.49
Unskilled & non-degree[a]	.88	.91
Bachelors	.079	.064
Post-graduate	.041	.031
Currently in labour force	.9	.75
Currently employed[b]	.95	.93
Average earnings[c]	29,601	30,072

Source: The International Adult Literacy Survey (New Zealand, 1996) and New Zealand Census of Population, 1996.
Note: [a] Combined because each level is defined differently in each data set. [b] Of the labour force.
[c] For paid employees, in current dollars.

The New Zealand sample included 2,481 individuals, 2,400 of whom were aged between 18 and 64. Compared with the 1996 Census, this sample is under-weighted, yet biased towards those who arguably have more hu-

[34] France withdrew its data in 1995 and Australia does not contribute to the common database. My analysis is thus restricted to 11 countries.

man capital: younger, Europeans, men and university graduates (Table 6.1). Labour-force participants and working individuals are also over-surveyed. Indeed, all respondents aged 18-64 were working or had held a job in the preceding 12 months. Only the difference in the income statistics is reasonable; income in the IALS is lower because it strictly refers to earnings.

The IALS measures three types of literacy: prose, document and numeracy (or quantitative). Prose literacy refers to the knowledge and skills needed to understand and use information from texts such as newspapers and fiction. Document literacy is the ability to locate and use information from maps, graphs, tables and forms. Numeracy literacy assesses the ability to perform arithmetic operations, such as balancing a chequebook or calculating the amount of interest on a loan. Each type of literacy is evaluated on a continuous scale ranging from 0 to 500.

The IALS literacy scores have been widely used as a measure of human capital.[35] According to Table 6.2, Sweden is the only country whose average scores exceed 300 points. Poland lags well behind other countries, while New Zealand belongs to the lower-middle ranking group. The three measures of literacy are strongly correlated with each other, but show little correlations with years of schooling. With an average educational attainment of 14 years, Americans are the most educated, whereas the highly literate Swedish are among the worst performers in this 'conventional' measure of human capital.

I assume that human capital is neither years of schooling, literacy scores, nor lifetime earnings. Rather, it is a latent variable that is reflected in such labour-market outcomes as earnings and how much time the person spends

[35]Examples include Coulombe et al. (2004); Murray (2005); OECD (1998).

Table 6.2: Proxies for human capital

	Literacy score			Years of
	Prose	Document	Numeracy	schooling
Belgium	279 (51)	287 (49)	292 (55)	12.6 (3.1)
Canada	290 (60)	293 (63)	294 (59)	13.1 (3.5)
Germany	278 (45)	289 (44)	296 (42)	11.6 (3.3)
Ireland	268 (55)	263 (57)	269 (61)	10.6 (3.1)
Netherlands	290 (40)	295 (41)	296 (43)	13.3 (4.0)
New Zealand	286 (51)	281 (52)	283 (51)	12.3 (2.8)
Poland	237 (54)	235 (65)	247 (64)	11.7 (2.9)
Sweden	306 (46)	310 (47)	311 (48)	11.9 (3.5)
Switzerland	271 (49)	279 (56)	287 (50)	12.5 (3.2)
United Kingdom	281 (50)	284 (55)	284 (55)	12.5 (2.7)
United States	288 (61)	282 (64)	289 (63)	13.8 (3.1)

Note: In parentheses are standard deviations. See Appendix Table 9 for further details.

on working. This latent human capital is shaped by parental education, educational achievement, demographic background and literacy skills.

By construction, parental education influences literacy skills both directly and indirectly through own education. First, if education 'signals' innate abilities and if intergenerational correlation in innate abilities is strong, children born to educated parents should be more able, thus having higher literacy skills. Second, educated people earn more and may also appreciate the value of education more. Hence, they would invest more in children's schooling, thereby raising children's educational achievement. Education, in turn, enhances literacy skills.

By definition, literacy abilities constitute human capital. Other possible determinants of human capital include parental education, own education and demographic background. These latent variables are meant to capture possible effects on human capital (of parental wealth, innate abilities, envi-

ronment, contacts and opportunities) that do not show up through literacy skills. Demographic variables include age and four dummies for male, migrant, native speaker and rural resident. Age also enters as a quadratic term to allow for possible non-linearity between age and human capital.

As in Chapters 3-4, my analysis focuses on the common age range in the labour force, from 18 to 64. Means and standard deviations of these variables are presented in Appendix Table 9.[36] At first glance, these summary statistics are broadly similar across countries. This is because these countries share many economic, demographic and institutional characteristics.

6.3 Model specification

My model for estimating human capital is illustrated by Figure 6.2 and can be specified as follows. The inner model:[37]

$$\text{Educational achievement} = \beta_{20} + \beta_{21}\text{Parental education} + \nu_2 \tag{6.11}$$

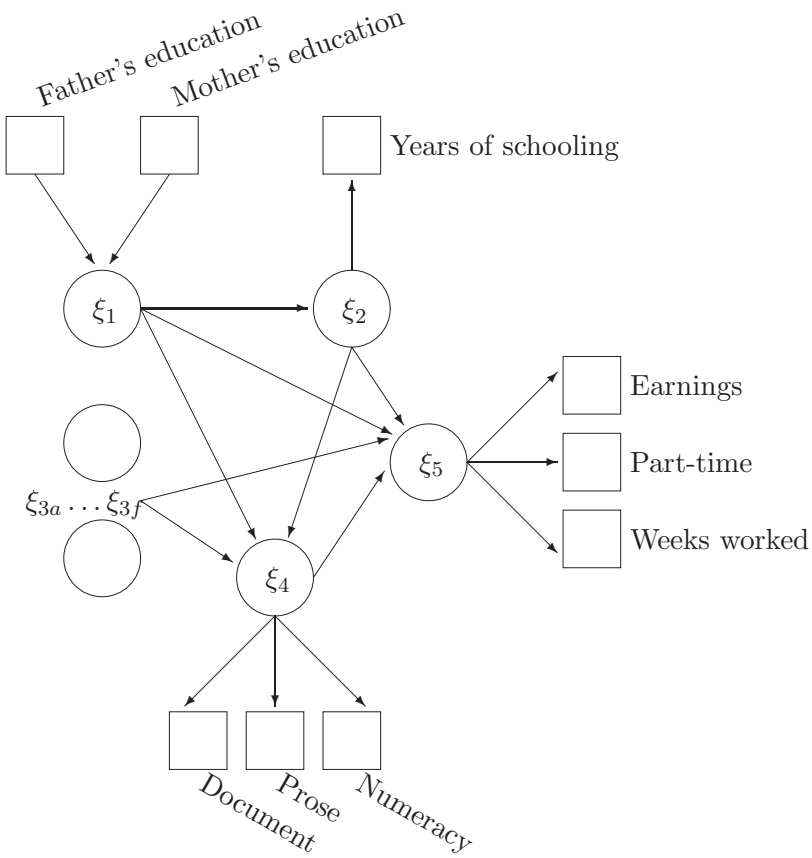
$$\begin{aligned}&\text{Literacy skills} = \beta_{40} + \beta_{41}\text{Parental education}\\&+ \beta_{42}\text{Educational achievement} + \beta_{43}\text{Demographic background} + \nu_4\end{aligned} \tag{6.12}$$

[36]Some variables, most notably earnings, are defined somewhat differently across countries. This should not be a concern, as the model is estimated separately for each country.

[37]In equations (6.12) and (6.13) 'demographic background' is used as shorthand for a set of six demographic latent variables.

$$\begin{aligned}\text{Human capital} = \beta_{50} \\ &+ \beta_{51}\text{Parental education} + \beta_{52}\text{Educational achievement} \\ &+ \beta_{53}\text{Demographic background} + \beta_{54}\text{Literacy skills} + \nu_5 \quad (6.13)\end{aligned}$$

Figure 6.2: A PLS model of human capital



Note: ξ_1 : Parental education, ξ_2 : Educational achievement
$\xi_{3a} \ldots \xi_{3f}$: Demographic background, ξ_4 : Literacy skills, ξ_5 : Human capital

In the outer model, parental education is estimated by mode B, while literacy skills and human capital are estimated by mode A. Educational achievement has only one manifest variable, namely years of schooling. Demographic background latent variables are their own manifest variables.

$$\begin{aligned}\text{Parental education} = \omega_{10} & \\ & + \omega_{11}\text{Father has no more than primary education} \\ & + \omega_{12}\text{Father has tertiary education} \\ & + \omega_{13}\text{Mother has no more than primary education} \\ & + \omega_{14}\text{Mother has tertiary education} \\ & + \delta_1\end{aligned} \tag{6.14}$$

$$\text{Document literacy} = \omega_{410} + \omega_{41}\text{Literacy skills} + \delta_{41} \tag{6.15a}$$

$$\text{Prose literacy} = \omega_{420} + \omega_{42}\text{Literacy skills} + \delta_{42} \tag{6.15b}$$

$$\text{Numeracy literacy} = \omega_{430} + \omega_{43}\text{Literacy skills} + \delta_{43} \tag{6.15c}$$

$$\text{Earnings} = \omega_{510} + \omega_{51}\text{Human capital} + \delta_{51} \tag{6.16a}$$

$$\text{Mostly work part time} = \omega_{520} + \omega_{52}\text{Human capital} + \delta_{52} \tag{6.16b}$$

$$\text{Weeks worked last year} = \omega_{530} + \omega_{53}\text{Human capital} + \delta_{53} \tag{6.16c}$$

6.4 Results

I use PLS-Graph version 3.0 by Chin (2001) to estimate the model in Section 6.3. The predictor specification in the inner and outer equations is an important part of the PLS model. Hence, before analysing point estimates

of the inner model, the outer model must first be examined on the extent to which it produces reliable results.

6.4.1 Outer model

Two criteria are used to assess the outer model: convergent and discriminant validity. Convergent validity checks if different manifest variables of the same latent variable agree with each other. The first measure of convergent validity is loadings. Gefen et al. (2000) suggest that only manifest variables with loadings greater than 0.4 are significant. The results for New Zealand (Table 6.3) show that all manifest variables meet this requirement. Convergent validity is also evaluated by composite reliability, an index capturing the internal consistency of each latent variable.[38] Generally, a value greater than 0.7 is acceptable (Fornell and Larcker, 1981). The last test for convergent validity is based on average variance extracted (AVE).[39] This index measures the amount of variance that is explained by the latent variable relative to the amount due to measurement error. According to Fornell and Larcker (1981), satisfactory latent variables should explain more than half of the variance, that is, the AVE should exceed 0.5. Table 6.4 (page 136) confirms that my outer model passes the last two tests comfortably.

AVE can also be used to judge discriminant validity. Discriminant validity indicates the degree to which latent variables can be distinguished from each other. For each latent variable, the square root of AVE is required to be greater than its correlation with another latent variable, meaning that

[38] Defined as $\left(\sum \pi_i\right)^2 \sigma_\xi / [\left(\sum \pi_i\right)^2 \sigma_\xi + \sum \sigma_{\epsilon_i}]$, where π_i is loading of x_i on ξ, ϵ_i is measurement error of x_i and σ denotes variance.

[39] Given by $\sum \pi_i^2 \sigma_\xi / \left(\sum \pi_i^2 \sigma_\xi + \sum \sigma_{\epsilon_i}\right)$.

Table 6.3: PLS estimates of the outer model

		T-statistic	
	Coefficient	Bootstrap	Jackknife
Outer model weights			
Parental education			
Father's edu $\leq$ primary	-0.27	3.4	1.7
Father's edu = tertiary	0.57	8.2	5.0
Mother's edu $\leq$ primary	-0.21	2.5	2.7
Mother's edu = tertiary	0.47	6.4	4.8
Outer model loadings			
Literacy skills			
Document literacy	0.98	1,128.1	805.6
Prose literacy	0.96	609.8	377.3
Numeracy literacy	0.97	655.3	444.0
Human capital			
Earnings	0.87	128.8	90.1
Working part time	-0.78	69.1	46.9
Weeks worked last year	0.66	39.3	27.2

Note: Bootstrap standard errors are based on 200 resamples. Jackknife t-statistics have been corrected for potential correlation between samples.

each latent variable shares more variance with its manifest variables than with other latent variables. Since the lowest AVE is 0.6, while the highest correlation among latent variables (excluding that between age and age squared, see Table 6.4) is 0.4, discriminant validity is well established. The low correlations between latent variables also preclude the possibility of multicollinearity.

Weights in the outer model express the effects on latent variables of their manifest variables. For example, relative to parents whose highest education is secondary, father having no more than primary schooling lowers the latent parental education ($\hat{\omega} = -0.27$), while father with a tertiary degree greatly enhances it ($\hat{\omega} = 0.57$). Loadings, by contrast, show the influence of latent

variables on their manifest variables. Document literacy loads 0.98 on literacy skills, meaning that one standard deviation increase in the latent literacy abilities would raise the observed document literacy score by 0.98 standard deviation. Similarly, people with higher human capital earn more, work longer hours and are much less likely to work part time. These weight and loading coefficients are both strong and highly significant.

6.4.2 Inner model

The inner model can be examined now that the outer model is validated. Central to this model are path coefficients, which illustrate the associations between latent variables. According to Table 6.5 (page 137), parental education has a positive impact on individuals' educational achievement, which in turn greatly influences their literacy. Parental education also directly affects literacy skills, though much less than its effect on educational achievement. Native speakers are clearly ahead in literacy skills, while men show no visible advantage over women. Migrants and rural residents tend to be less literate, but only marginally. The paths on age and age squared have opposite signs, implying that age raises literacy skills at a diminishing rate.

Human capital is also concave in age, and much more so than literacy skills. Literacy yields a strong effect on human capital; the latter rises by 0.17 standard deviation for every one standard deviation increase in the former. The largest gap in human capital is observed between men and women ($\hat{\beta} =$ 0.41 for male). Being migrant now has a positive, yet trivial, association with human capital. Own education and parental education have minimal

effects once literacy is controlled for. The influence of language skills and rural residence on human capital is also negligible.

Standard errors are calculated by two resampling methods: bootstrap and jackknife. Bootstrap draws B random samples, *with replacement*, of m observations from the original data set. The model parameters are then re-estimated with each sample. Jackknife is a special case of bootstrap but *without replacement*, where one observation is omitted from the sample at a time. The jackknife t-statistics in Table 6.5 are 'conservative,' as they have been adjusted for possible interdependence between samples.

Most variables are statistically significant. Educational achievement does not only produce the strongest effect on literacy skills but also has the highest t-statistic. Gender is the most significant explanatory variable of human capital. Yet bootstrap and jackknife standard errors differ markedly, sometimes leading to opposite conclusions. For example, the bootstrap method suggests that gender is not a significant variable ($t = 0.1$) in explaining literacy skills, while the jackknife approach finds it highly significant ($t = 13.8$). Contradictory results are also apparent for native speaking and migrant status in the human capital equation. However, this contradiction creates little impact, as it applies only to variables whose path coefficients are virtually zero.

The R^2 coefficient, as in OLS regressions, indicates the amount of variance predicted by the model. My model explains 24 percent of the variation in literacy skills and 27 percent for human capital. These ratios show high predictive power, given the complexity of model. A decomposition in Table 6.6 (page 138) suggests that the essence of the model is captured by one

or two major variables. These key variables are those with the strongest paths and the greatest statistical significance identified above. In particular, 62 percent of the explained variation in literacy skills is due to educational achievement alone. Another 30 percent is predicted by parental education and language advantage, whereas age, migrant status and residence location add minimal predictive power. Gender has no effect on literacy skills but it accounts for 62 percent of the explained variation in human capital. Age is the second most important determinant of human capital, while the presence of other demographic variables (migrant status, language skills, and region of residence) makes little difference. Overall, age, gender and education capture 85 percent of the human capital model.

These results are by no means unique to New Zealand. The above patterns in paths, standard errors and R^2's repeat for other countries. Educational achievement is always the single most influential determinant of literacy skills, while gender, age and education are the key predictors of human capital. Appendix Table 10 shows that educational achievement captures from 50 percent (Germany) to 79 percent (Ireland) of the explained variation in literacy skills. The contribution of age, gender and education to explained variation in human capital ranges from 65 percent (Ireland) to 97 percent (Belgium, Poland and United Kingdom).

These findings concur with those in Chapter 4, where human capital exhibits concavity in age and varies enormously across ethnicity, gender and education. This agreement suggests that the model in Chapter 4 is reasonably reliable. Of course, the current model may not incorporate all possible determinants. Nevertheless, I have used all relevant variables that are avail-

able from a typical socio-economic survey, so these results lend credence to those in Chapter 4. It is true that determinants of human capital are not just age, gender and education; yet these variables prove to account for most of the explained variation in human capital. Human capital is obviously not just education or literacy abilities. Education only represents a potential, and how much of that potential is turned into productive capital depends on several factors. Age is important, as it proxies for work experience, a key determinant of productivity. Gender is associated with availability for work. Indeed, despite recent movements in the work force, women are still less likely to participate in the labour force and tend to work fewer hours. In countries like New Zealand, where there is little inequality in literacy and education (as measured by years of schooling, see Table 6.2), these education-based indicators inadequately represent people's actual productive capacity. Clearly, I have adopted a human capital concept that is labour market oriented. Human capital defined differently may be influenced by different factors.

Table 6.4: Correlations between latent variables

		Composite reliability	AVE	ξ_1	ξ_2	ξ_{3a}	ξ_{3b}	ξ_{3c}	ξ_{3d}	ξ_{3e}	ξ_{3f}	ξ_4
ξ_1.	Parental education			1.00								
ξ_2.	Educational achievement			0.30								
ξ_{3a}.	Age			-0.25	-0.09							
ξ_{3b}.	Age squared			-0.25	-0.09	0.99						
ξ_{3c}.	Male			0.01	-0.01	-0.01	-0.00					
ξ_{3d}.	Migrant			0.08	0.10	0.07	0.06	0.00				
ξ_{3e}.	Native speaker			0.02	-0.05	0.04	0.04	0.02	-0.35			
ξ_{3f}.	Rural			-0.10	-0.17	0.09	0.08	0.03	-0.13	0.09		
ξ_4.	Literacy skills	0.98	0.94	0.25	0.41	-0.04	-0.06	-0.00	-0.05	0.19	-0.09	
ξ_5.	Human capital	0.82	0.60	0.00	0.12	0.15	0.12	0.40	0.01	0.07	-0.05	0.21

Note: Composite reliability and AVE are not applicable to parental education because it is estimated by mode B. Educational achievement and demographic background latent variables have only one manifest variable each, so their composite reliability and AVE are 1.

Table 6.5: PLS estimates of the inner model

		T-statistic	
	Path coefficient	Bootstrap	Jackknife
Educational achievement			
Parental education	0.30	13.1	0.0
Literacy skills			
Parental education	0.14	6.0	5.6
Educational achievement	0.37	20.6	26.6
Age	0.70	6.1	6.0
Age squared	-0.68	5.9	2.4
Male	0.00	0.1	13.8
Migrant	-0.04	2.2	24.5
Native speaker	0.20	8.6	4.2
Rural	-0.04	2.2	4.4
Human capital			
Parental education	0.04	1.9	10.9
Educational achievement	0.06	2.8	10.4
Age	1.25	10.3	2.1
Age squared	-1.11	9.0	0.5
Male	0.41	24.6	13.3
Migrant	0.01	0.3	3.1
Native speaker	0.04	1.8	10.3
Rural	-0.07	3.6	31.9
Literacy skills	0.17	9.2	4.3

Note: See Table 6.3 (page 131).

Table 6.6: Contribution of each latent variable in explaining literacy skills and human capital

	Path coef.	Correlation	% contrib. to R^2
Literacy skills ($R^2 = 0.24$)			
Parental education	0.14	0.25	14.5
Educational achievement	0.37	0.41	62.4
Age	0.70	-0.04	-11.6
Age squared	-0.68	-0.06	16.7
Male	0.00	-0.00	-0.0
Migrant	-0.04	-0.05	0.9
Native speaker	0.20	0.19	15.8
Rural	-0.04	-0.09	1.4
Human capital ($R^2 = 0.27$)			
Parental education	0.04	0.00	0.0
Educational achievement	0.06	0.12	2.5
Age	1.25	0.15	68.4
Age squared	-1.11	0.12	-47.8
Male	0.41	0.40	61.5
Migrant	0.01	0.01	0.0
Native speaker	0.04	0.07	1.1
Rural	-0.07	-0.05	1.4
Literacy skills	0.17	0.21	13.2

Chapter 7

Summary and conclusions

This study presents new estimates of human capital using a lifetime labour income approach. For the New Zealand population aged 18-64, human capital, as measured by lifetime labour income, averaged 356,000 per person in 2001. This figure reflects persistent growth from previous years, specifically by 4.2 percent from 1996 and by 23 percent from 1981.

Age is the most important determinant of lifetime income. Lifetime income rises for the first few years and declines steadily thereafter. The age gradient of income profiles is steeper for men and for tertiary degree holders, while the age at which lifetime income peaks depends heavily on education and ethnicity.

Education makes a huge difference to human capital. People who left school before the sixth form have half as much human capital as non-degree holders, and only one third of Bachelors graduates. Returns to education diminish, though, as having a post-graduate qualification produces no more than an 11 percent premium over a Bachelors degree. The gap in human

capital between university graduates and non-graduates has widened over time, indicating that skill premia have risen.

The gender gap is sizeable, even though it has narrowed noticeably. In 1981, women's average human capital was only 43 percent of men's, but this ratio increased to 66 percent in 2001. The extent of gender inequality lessens in more educated groups; for non-European university graduates, women even had more human capital than men in 2001.

Contrary to the gender gap, the ethnic gap has broadened. In 2001, non-Europeans had 48 percent less human capital than Europeans, while this difference was only 32 percent in 1981. Apparently, the ethnic gap in human capital is exacerbated by the fact that non-Europeans are less educated than Europeans; within each gender-education cohort, the human capital disadvantage for non-Europeans could be as low as 5 percent.

The total stock of human capital was worth $811 billion in 2001. Women's share in this stock rose steadily, from 30 percent in 1981 to 41 percent 20 years later. Most of this growth stems from the fact that women have approached men in education and labour-force participation. The human capital embodied in university graduates almost quadrupled; in relative terms, their share soared from 9 percent to 23 percent. Even though the ethnic gap in per capita human capital expands, non-Europeans' share in total human capital has continually grown, because the share of purely Europeans in the population has shrunk. All of the above results are robust to various modelling assumptions, although more extreme variations could be tested.

Between 1981 and 2001, New Zealand's stock of human capital increased by 56 percent, primarily due to the expansion of the labour force. Migration

contributed 8.3 percent. Educational investment accounted for 1 percent. Another 2.9 percent originated from changes in the labour market. The balance was attributable to aging and mortality.

Compared with physical capital, New Zealand's economically effective human capital stock is well over double, reaching 2.6 in 2001. However, this comparison is rather superficial, as physical capital is measured by its cost and is net of maintenance expenses, whereas human capital in this study is measured by its yield and is in gross terms.

My results are subject to a few qualifications. First, my study focuses on the human capital of working people and neglects idle capital, which may not be completely worthless. Such an omission may understate the value of the human capital stock, but how to take appropriate account of non-market human capital is a contentious issue. Second, my estimates rest crucially on the assumptions that wages mirror labour productivity and that labour productivity is a good measure of human capital. In practice, wages may diverge from productivity, thereby biasing my results.

Biases may also arise because some important variables, such as innate ability and family background, were overlooked. My partial defence lies with the PLS approach, which shows that age, gender and education capture some 85 percent of the explained variation in human capital. Even though my PLS model may not encompass all relevant factors, it sheds light on the significance of various variables in explaining human capital. Also, however large the omitted variables bias is, it would only be of concern to results for individuals and would make no difference to population aggregate estimates.

This approach requires extensive data on earnings, employment, educational enrolment and mortality rates, which are only available from the census. It is also very computationally demanding. However, the method offers a comprehensive measure which accounts for the heterogeneity of labour. By evaluating knowledge and skills at the market rate, this model measures the amount of human capital that is being utilised, rather than simply summing up the acquired capital. Being in dollars and cents, this measure also conveys meaningful economic interpretation.

My results provide only the fourth country-specific monetary measure of human capital. Unfortunately, direct comparisons with existing international evidence are not possible, due to differences in methods and assumptions. Nevertheless, these findings help to establish whether patterns exist for, say, the relative sizes of physical and human capital stocks in developed countries. The approach and new results presented here contrast with the 'numerous' attempts to create measures based upon educational experience. Hopefully, this will encourage others to produce time series of monetary measures of human capital for other countries to aid empirical research on the determinants of economic growth.

Glossary

average variance extracted measures the amount of variance that is explained by the latent variable relative to the amount due to measurement error

block a set of manifest variables that are associated with a specific latent variable

composite reliability measures the internal consistency of each latent variable

construct = latent variable

convergent validity evaluates if different manifest variables of the same latent variable agree with each other

discriminant validity evaluates the degree to which latent variables can be distinguished from each other

formative mode = mode B

indicator = manifest variable

inner model describes relationships between latent variables

inward mode = mode B

item = manifest variable

latent variable an unobservable, not directly measurable variable

loading effect of a latent variable on a manifest variable

location 'intercept' of an inner model or outer model

manifest variable a measurable variable that is used to (indirectly) measure a latent variable

measurement model = outer model

mode A a regression using a latent variable to explain each of its manifest variables

mode B a regression in which a latent variable is explained by its manifest variables

mode C PLS algorithm in which each of mode A and mode B is used at least once

outer model describes relationships between a latent variable and its manifest variables

outward mode = mode A

path coefficient effect of one latent variable on another

path model = inner model

reflective mode = mode A

structural model = inner model

weight effect of a manifest variable on a latent variable

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Appendices

Appendix Table 1: Summary of studies on measuring human capital using cost-based, income-based and integrated approaches

Source	Method	Country, time	Motivation	Results
Petty (1690)	Income-based	England and Wales	-Interest in public finance -To evaluate the power of England, the economic effects of migration, the loss caused by a plague or by men killed in war	Aggregate stock was about £520 million, or £80 per capita.
Farr (1853)	Income-based	England	Interest in public finance: taxing human capital	Net value of per capita human capital was about £150.
Engel (1883)	Cost-based	Germany		
Wittstein (1867)	Income-based (Farr's approach), combined with cost-based (Engel's approach)	Germany	To determine a guide to be based on for claims for compensation from loss of life	
Nicholson (1891, 1896)	Income-based, combined with cost-based	United Kingdom, 1891	To estimate the stock of "living" capital	The stock of living capital was about 5 times that of conventional capital.

Source	Method	Country, time	Motivation	Results
De Foville (1905)	Income-based (Petty's approach)	France, around 1900		
Fisher (1908)	Income-based (Farr's approach)	United States (US), 1907	To estimate the cost of preventable illness and death	The stock of human capital exceeded all other wealth.
Barriol (1910)	Income-based (Farr's approach)	France and other selected countries	To estimate the social value of an individual	
Huebner (1914)	Income-based (Farr's approach)	US, around 1914		The stock of human capital was 6-8 times that of conventional capital.
Wickens (1924)	Income-based (Farr's approach)	Australia, 1915		The human capital stock of £6,211 million (or £1,246 per capita) was about 3 times as large as the physical capital stock.
Woods and Metzger (1927)	5 different methods, including -Farr's approach -Petty's approach	US, 1920	To show the importance of the nation's population	
Dublin (1928)	Unknown	US, 1922		The stock of human wealth was about 5 times that of material wealth.

Source	Method	Country, time	Motivation	Results
Dublin and Lotka (1930)	Income-based (improved from Farr's approach)		-To estimate how much life insurance a man should carry -To estimate the economic costs of preventable disease and premature death	
Schultz (1961a)	Cost-based	US, 1900-1956	Economic growth, productivity	The stock of human capital grew twice as fast as that of physical capital.
Weisbrod (1961)	Income-based	US, 1950, males aged 0-74	To estimate the value of the human capital stock	-Gross: \$1,335b at $i = 10\%$, \$2,752b at $i = 4\%$ -Net (of consumption): \$1,055b and \$2,218b respectively -Compared with non-human assets of \$881b
Kendrick (1976)	Cost-based	US, 1929-1969	To develop national wealth estimates to complement estimates of the physical stock in the national accounts	The stock of human capital was often greater and grew faster than that of physical capital.
Graham and Webb (1979)	Income-based	US, 1969, males aged 14-75	National accounts	The stock of human capital ranged from \$2,910 billion at 20% discount rate to \$14,395 billion at 2.5% discount rate. This contrasted with an estimate of \$3,700 billion that Kendrick (1976) obtained based on the cost method.

Source	Method	Country, time	Motivation	Results
Eisner (1985)	Cost-based	US, 1945-1981 (selected years)	To implement the total incomes system of accounts	The stock of human capital was almost as large as that of physical capital.
Jorgenson and Fraumeni (1989, 1992)	Income-based	US, 1947-1986	-To present a new system of national accounts for the US economy -To measure the output of the education sector	The stock of human capital almost doubled between 1949-1984. Per capita human capital grew by only 15% during 1947-1986. Women's share was around 40%. The share of human capital based on market activities was around 30%. Human capital was 12-16 times greater than physical capital in size. For the period 1948-1969, their (1992) estimates were from 17.5 to 18.8 times higher than Kendrick's (1976).
Ahlroth et al. (1997)	Income-based (Jorgenson and Fraumeni's method)	Sweden, 1968, 1974, 1981 and 1991	To derive the aggregate measures of the output of the Swedish education sector that can serve as alternatives to the input-based measures that are traditionally used in the national accounts	Even the lowest estimates of the human capital stock (after taxes, excluding leisure income) were 6-10 times higher than the stock of physical capital.

Source	Method	Country, time	Motivation	Results
Macklem (1997)	Income-based (macro focused)	Canada, 1963-1994, quarterly	To provide a comprehensive measure of aggregate private sector wealth that includes both human and non-human components	Per capita human wealth rose steeply from 1963 to 1973, then decreased well into the mid-1980s, but has picked up since. The ratio of aggregate human wealth to non-human wealth fell from 8:1 in the early 1960s to about 3:1 in the 1990s.
Mulligan and Sala-i-Martin (1997)	Income-based	48 US continental states, 6 census years (1940, 1950, 1960, 1970, 1980, 1990)	To provide an alternative measure of human capital	The stock of human capital shrank substantially between 1940 and 1950, then rose steadily to 1990. Between 1980 and 1990, the stock of human capital increased by 52%, whereas over the 4 earlier decades it grew by only 17%.
Tao and Stinson (1997)	Integrated	US, 1963-1988, employed work force	To provide an alternative approach to human capital measurement which circumvents the problems of the cost- and income-based approaches	The effective human capital stock expanded by 6 times. When differences in the abilities of base entrants are considered, the growth dropped to less than 100%. The expansion was greater for females (135%) than for males (75%), largely due to the increased labour-force participation by the former.
Koman and Marin (1999)	Income-based	Austria and Germany, aged 15 and over, 1960-1997	To assess the impact of human capital on economic growth	Human capital grew over twice as fast as average years of schooling.

Source	Method	Country, time	Motivation	Results
Dagum and Slottje (2000)	Integrated	US, 1982	To estimate the monetary value of personal human capital and to examine its size distribution	Average human capital ranged from $239,000 to $365,000. In real terms, their lowest estimate is still twice Kendrick's (1976) estimate for 1969, but well below those obtained by Jorgenson and Fraumeni (1989, 1992) and Macklem (1997).
Laroche and Mérette (2000)	Income-based (Koman and Marin's (1999) method)	Canada, aged 15-64, 1976 to 1996	To provide an alternative measure of human capital	While average years of schooling increased by 15%, human capital, as measured by Koman and Marin's method, grew by 33%. When experience is accounted for, average human capital increased by up to 45%.
Jeong (2002)	Income-based (Mulligan and Sala-i-Martin's (1997) method)	45 countries	To compare human capital inputs for countries of diverse output levels	The richest countries have from 2.2 to 2.8 times as much human capital as the poorest countries.
Wei (2003)	Income-based (Jorgenson and Fraumeni's method)	Australia, aged 25-65, 1981-2001 quinquennially	To present systematic estimates of the stock of human capital for Australia	The stock of human capital increased by 75%. Women's share was approximately 40%. The stock of human capital was 3 times as large that of physical and this ratio has been rising.

Appendix Table 2: Summary of studies on measuring human capital using an education-based approach

Source	Data coverage	Population base	Method of constructing average years of schooling	Highlighted results
Psacharopoulos and Arriagada (1986)	99 countries, various years from 1960 to 1983	Labour force	$\overline{S} = D_p(\frac{1}{2}L_{p1} + L_{p2}) + (D_p + \frac{1}{2}D_s)L_{s1} + (D_p + D_s)L_{s2} + (D_p + D_s + D_h)L_h$ where $\overline{S}$ = average years of schooling, L_i = share of the labour force with the ith level of schooling, $i = p1$ for incomplete primary, $p2$ for complete primary, $s1$ for incomplete secondary, $s2$ for complete secondary, and h for higher, D = duration in years of the ith level, and i refers to primary (p), secondary (s) and higher education (h)	Top 5 countries: US 12.6 D R Germany 11.9 Canada 11.7 **New Zealand** 11.7 Czechoslovakia 11.5
Kyriacou (1991)	113 countries, for 1965, 1970, 1975, 1980, 1985	Labour force	$S_{1975} = \beta_1 + \beta_2 \times Prim_{1960} + \beta_3 \times Sec_{1970} + \beta_4 \times High_{1970}$ where $Prim, Sec, High$ = enrolment ratios for primary, secondary and higher education respectively, $\beta_1 = 0.052$, $\beta_2 = 4.439$, $\beta_3 = 2.665$, $\beta_4 = 8.092$	Top 5 countries in 1985: US 12.09 Finland 10.83 Germany 10.33 Israel 10.03 Canada 9.98

Source	Coverage	Population	Method	Highlights
Lau et al. (1991)	58 developing countries, 1965-1985	Working-age population (15-64)	$S_T = \sum_{T-a_{\min}+6}^{T-a_{\max}+6} \sum_{g=1}^{g_{\max}} E_{g,t}\theta_{g,t}$ where $S_T =$ total stock of education at year T $E =$ enrolment number of grade g at time t $\theta_{g,t} =$ probability that an enrolee will survive to year T $a_{\min} =$ 15, youngest working age $a_{\max} =$ 64, oldest working age $6 =$ school entry age	
Barro and Lee (1993)[a]	129 countries, 5-yearly periods from 1960 to 1985	Population aged 25 and over	$\overline{S} = D_p(\frac{1}{2}h_{ip} + h_{cp}) + (D_p + D_{s1})h_{is} + (D_p + D_{s1} + D_{s2})h_{cs} + (D_p + D_{s1} + D_{s2} + \frac{1}{2}D_h)h_{ih} + (D_p + D_{s1} + D_{s2} + D_h)h_{ch}$ where h_j = share of the adult population with the highest level of schooling j, $j = ip$ for incomplete primary, cp for complete primary, is for first cycle secondary, cs for second cycle secondary, ih for incomplete higher, and ch for complete higher, D = duration in years of the ith level, and i refers to primary (p), first cycle secondary ($s1$), second cycle secondary ($s2$) and higher education (h)	Top 5 countries in 1985: **New Zealand** 12.04 US 11.79 Hungary 10.75 Norway 10.38 Canada 10.37

Source	Coverage	Population	Method	Highlights
Nehru et al. (1995)[b]	85 countries, 1960-1987	Working-age population (15-64)	$S_T = \sum_{T-a_{\max}+6}^{T-a_{\min}+6} \sum_{g=1}^{g_{\max}} E_{g,t}(1 - r_{g,t} - d_{g,t})\theta_{g,t}$ where $r_{g,t}$ = repetition rates $d_{g,t}$ = dropout rates	Top 5 countries in 1987: Israel 12.58 US 11.62 Japan 10.99 Great Britain 10.21 Canada 10.01
Ahuja and Filmer (1995)	81 developing countries, for 1985, 1990, 1995	Population aged 6-60	Built on data from Barro and Lee (1993)	In 1995: High: 6.9 (East Asia and the Pacific) Low: 4.0 (Sub-Saharan Africa)
Barro and Lee (1996)[c]	126 countries, 5-yearly periods from 1960 to 1990	Population aged 15 and over	Revised from Barro and Lee's (1993) data	Top 5 countries in 1990: US 11.74 **New Zealand** 11.25 Denmark 10.70 USSR 10.50 Australia 10.39
De la Fuente and Doménech (2000)	21 OECD countries, 5-yearly periods from 1960 to 1990	Population aged 25 and over	Revised from Barro and Lee's (1996) data	Top 5 countries in 1990: Germany 12.99 US 12.91 Canada 12.80 Switzerland 12.53 Australia 12.28

Source	Coverage	Population	Method	Highlights
Cohen and Soto (2001)[d]	95 countries, 10-year intervals from 1960 to 2010	Population aged 15-64	Revised from Barro and Lee's (1996) data	Top 5 countries in 2000: UK 13.12 Australia 13.09 Canada 13.07 Germany 12.95 Switzerland 12.73
Barro and Lee (2001)[e]	142 economies, 5-yearly periods from 1960 to 2000	Population aged 15 and over	Revised from Barro and Lee's (1996) data	Top 5 countries in 2000: US 12.05 Norway 11.85 **New Zealand** 11.52 Canada 11.62 Sweden 11.41
Krueger and Lindahl (2001)	34 countries, mostly surveyed in 1990	Labour force	Derived from The World Values Survey	Top 5 countries: Norway 13.43 US 13.26 Sweden 12.79 Finland 12.61 Canada 12.60

Sources: [a]*Barro-Lee Data Set: Educational Attainment Data, 1960-1985, International Comparisons of Educational Attainment*, `http://www.worldbank.org/research/growth/ddbarlee.htm`
[b]*Nehru and Dhareshwa Data Set*, `http://www.worldbank.org/research/growth/ddnehdha.htm`
[c]*Barro-Lee Data Set, International Measures of Schooling Years and Schooling Quality*, `http://www.worldbank.org/research/growth/ddbarle2.htm`
[d]Data available at `http://www.oecd.org/dataoecd/33/13/2669521.xls`
[e]Data available at `http://www.cid.harvard.edu/ciddata/Appendix%20Data%20Tables%20-%20in%20Panel%20Set%20format.xls`

Appendix Table 3: Average years of schooling: New Zealand in comparison with Australia and the United States

Source	Year	Countries	New Zealand		Australia		United States	
Psacharopoulos and Arriagada (1986)	1981*	99	11.7	3	11.1	8	12.6	1
Kyriacou (1991)	1965	80	7.97	5	6.91	8	9.82	1
	1970	89	7.94	6	7.39	10	10.40	1
	1975	109	8.31	9	7.81	15	11.95	1
	1980	109	8.79	11	8.26	15	12.02	1
	1985	113	9.28	12	8.72	18	12.09	1
Barro and Lee (1993)	1960	101	9.61	1	8.93	3	8.67	4
	1965	98	9.54	1	8.94	4	9.36	3
	1970	102	9.69	3	10.09	2	10.14	1
	1975	108	11.16	1	10.01	4	10.77	2
	1980	110	12.14	1	10.08	7	11.89	2
	1985	106	12.04	1	10.24	7	11.79	2
Barro and Lee (1996) (Population aged 25+)	1960	107	9.55	2	9.03	3	8.66	5
	1965	107	9.42	2	8.94	4	9.25	3
	1970	109	9.37	4	10.09	1	9.79	3
	1975	114	11.00	1	9.81	4	10.01	3
	1980	113	11.94	1	10.02	6	11.91	2
	1985	113	11.88	1	10.06	5	11.71	2
	1990	112	11.18	3	10.12	8	12.00	1
Barro and Lee (1996) (Population aged 15+)	1960	107	9.70	3	9.28	4	8.49	5
	1965	107	9.74	2	9.18	4	9.09	5
	1970	109	9.72	3	10.24	1	9.56	5
	1975	114	11.27	1	10.14	2	9.69	6
	1980	114	11.94	1	10.29	4	11.86	2
	1985	114	11.91	1	10.32	4	11.56	2
	1990	113	11.25	2	10.39	5	11.74	1

Source	Year	Countries	New Zealand		Australia		United States	
Nehru et al. (1995)	1960	83 each year	5.70	21	6.00	19	10.73	2
	1961		5.76	21	5.98	19	10.72	2
	1962		5.82	21	5.97	19	10.70	2
	1963		5.89	21	5.96	20	10.68	2
	1964		5.96	21	5.96	20	10.67	2
	1965		6.03	20	5.97	22	10.66	2
	1966		6.14	21	5.99	22	10.67	2
	1967		6.26	21	6.03	22	10.68	2
	1968		6.38	21	6.07	22	10.69	2
	1969		6.46	20	6.12	22	10.70	2
	1970		6.55	20	6.16	22	10.71	2
	1971		6.66	20	6.24	22	10.74	2
	1972		6.76	20	6.31	21	10.75	2
	1973		6.88	20	6.39	21	10.77	2
	1974		6.99	19	6.46	21	10.78	2
	1975		7.11	19	6.54	21	10.80	2
	1976		7.24	17	6.63	21	10.84	2
	1977		7.38	17	6.72	21	10.88	3
	1978		7.53	17	6.81	21	10.92	2
	1979		7.68	17	6.91	21	10.96	2
	1980		7.82	17	6.98	22	10.98	2
	1981		7.97	17	7.08	22	11.09	2
	1982		8.11	16	7.16	22	11.19	2
	1983		8.24	14	7.24	23	11.28	2
	1984		8.38	13	7.32	24	11.35	2
	1985		8.51	13	7.40	24	11.41	2
	1986		8.68	11	7.50	24	11.52	2
	1987		8.85	11	7.60	25	11.61	2
De la Fuente and Doménech (2000)	1960	21 each year	10.46	3	10.15	4	11.44	2
	1965		10.72	3	10.67	4	11.69	2
	1970		10.98	4	11.15	3	11.93	2
	1975		11.30	4	11.43	3	12.24	1
	1980		11.60	5	11.71	3	12.53	2
	1985		11.86	6	12.00	4	12.74	1
	1990		12.11	6	12.28	5	12.91	2

Source	Year	Countries	New Zealand		Australia		United States	
Barro and Lee (2001) (Population age 25+)	1960	99	9.55	1	9.43	2	8.66	4
	1965	99	9.42	1	9.30	2	9.25	3
	1970	101	9.36	3	10.09	1	9.79	2
	1975	106	11.00	1	9.81	3	10.01	2
	1980	105	11.43	2	10.02	5	11.91	1
	1985	105	11.43	2	10.06	4	11.71	1
	1990	107	11.18	2	10.12	6	12.00	1
	1995	104	11.31	3	10.31	6	12.18	1
	2000	104	11.52	3	10.57	6	12.25	1
Barro and Lee (2001) (Population age 15+)	1960	99	9.70	2	9.73	1	8.49	5
	1965	99	9.74	1	9.57	2	9.09	3
	1970	101	9.72	2	10.24	1	9.53	4
	1975	106	11.27	1	10.14	2	9.69	4
	1980	106	11.47	2	10.29	5	11.87	1
	1985	107	11.50	2	10.32	4	11.57	1
	1990	109	11.25	3	10.38	5	11.74	1
	1995	105	11.49	3	10.67	6	11.89	1
	2000	105	11.74	3	10.92	6	12.05	1
Cohen and Soto (2001)	1960	95 each year	8.98	10	9.82	3	10.18	2
	1970		9.87	11	11.04	4	11.27	2
	1980		10.72	11	12.20	3	12.19	4
	1990		11.02	11	12.76	3	12.62	4
	2000		12.09	11	13.09	2	12.63	6
	2010		12.48	10	13.25	4	13.24	5

Note: Entries for each country are respectively average years of schooling and ranking for the applicable year. *1981 for these 3 countries, but other years may apply to others.

Appendix Table 4: Lee and Barro's data on indicators of schooling inputs and outcomes

Indicator	1960		1965		1970		1975		1980		1985		1990	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
No. of sch. days per year (Primary)	200 (44)	195	(in general, not indicative of year 1960)											
No. of sch. hours per year (Prim.)	1000 (30)	980												
Pupil/Teacher ratio (Prim.)	30.9 (38)	29.3	25.2 (25)	25.8	21.3 (14)	24.1	18.5 (11)	21.1	16.7 (13)	19.0	19.9 (30)	17.5	18 (28)	15.7
Pupil/Teacher ratio (Secondary)	19.4 (67)	18.2	25.2 (113)	17.2	24.4 (107)	16.2	29.1 (117)	16.2	26.3 (104)	15.2	18.8 (61)	13.6	17.2 (52)	12.7
Govt. edu. exp. per pupil (Prim.) (1)	407 (10)	546	747 (15)	1,010	1,031 (10)	1,180	1,359 (14)	1,687	1,680 (10)	2,239	1,730 (15)	2,472	1,894 (16)	2,796
Govt. edu. exp. per pupil (Sec.) (2)	743 (24)	757	648 (43)	1,287	810 (42)	1,515	1,025 (29)	1,885	1,490 (23)	2,277	1,243 (27)	2,485	1,665 (22)	2,697
(1) to GPD per capita (%)	5.1 (58)	9.22	8.2 (73)	13.2	11 (45)	13.2	13 (40)	17.1	16.4 (28)	19.9	15.3 (30)	20.0	16.5 (15)	20.1
(2) to GPD per capita (%)	9.4 (62)	12.9	7.2 (83)	17.9	8.7 (86)	17.8	9.8 (81)	19.2	14.5 (67)	20.6	11 (69)	20.7	14.5 (58)	20.2
Avg. real salary of teachers (Prim.) (3)	8,676 (15)	10,428	13,921 (14)	17,873	16,461 (16)	19,811	21,813 (12)	25,922	24,327 (10)	25,725	25,903 (12)	28,821	18,279 (25)	28,372
(3) to GDP per capita (%)	1.09 (65)	1.89	1.54 (82)	2.48	1.76 (79)	2.31	2.08 (65)	2.73	2.37 (50)	2.44	2.29 (53)	2.51	1.59 (57)	2.10
Repetition rate (Prim.) (%)	.	.	0 (1)	5.65	0 (1)	5.48	0 (1)	4.26	4 (35)	3.91	3 (30)	3.77	3 (28)	3.14
Repetition rate (Sec.) (%)	.	.	.	.	3 (9)	8.31	.	9.50	3 (16)	9.28	2 (10)	12.1	2 (13)	11.3

Indicator	1960		1965		1970		1975		1980		1985		1990	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Dropout rate (Prim.) (%)	.	.	.	.	3 (17)	3.58	3 (18)	3.37	3 (19)	3.36	3 (20)	3.33	3 (21)	2.95

Source: Lee and Barro (2001) and *Barro-Lee Data Set, International Measures of Schooling Years and Schooling Quality*, `http://www.worldbank.org/research/growth/ddbarle2.htm`

Note: (a) New Zealand, (b) OECD average. Overall sample size is 145 countries, but data on the indicators are not always available for all countries. OECD averages are unweighted averages over 23 OECD countries. Numbers in brackets under New Zealand estimates are ranking for New Zealand; the lower the rank, the better New Zealand performs relatively to other countries. Statistics in (1), (2) and (3) are in 1985 US dollars adjusted for PPP.

Appendix Table 5: Barro and Lee's data on test scores

Test	Test participants	Top 5 countries	Results for NZ	
			Test score	Rank[a]
Mathematics (1982-83)	13 year-old students	Japan, Netherlands, Hungary, France, Belgium	46.4	10/17
Mathematics (1982-83)	FS students[b]	Hong Kong, Japan, Finland, Sweden, New Zealand	49.8	5/12
Mathematics (1993-98)	13 year-old students	Singapore, Korea, Japan, Hong Kong, Belgium	47.2	23/37
Science (1970-72)	14 year-old students	Japan, Hungary, Australia, New Zealand, Germany	30.3	4/16
Science (1970-72)	FS students	New Zealand, Germany, Australia, Netherlands, UK	48.3	1/16
Science (1993-98)	13 year-old students	Czech, Bulgaria, Singapore, Slovak, Russia	48.1	26/37
Reading (1990-91)	9 year-old students	Finland, US, Sweden, France, Italy	52.8	6/26
Reading (1990-91)	13 year-old students	Finland, France, Sweden, New Zealand, Switzerland	54.5	4/30
TIMSS[c] (1994-95): Math	7th grade students	Singapore, Korea, Japan, Hong Kong, Czech	472	23/37
TIMSS: Science	(as above)	Singapore, Korea, Czech, Japan, Bulgaria	481	23/37
IALS: Prose	Adults aged 16-65[d]	Sweden, Finland, Norway, Netherlands, Canada	275.2	7/20
IALS: Document	(as above)	Sweden, Norway, Denmark, Finland, Netherlands	269.1	12/20
IALS: Quantitative	(as above)	Sweden, France, Denmark, Norway, Germany	270.7	13/20

Source: Barro-Lee Data Set, International Measures of Schooling Years and Schooling Quality, `http://www.worldbank.org/research/growth/ddbarle2.htm`, and Barro and Lee (2001, Table 6).

Note: Overall sample size is 58 countries, but data on the tests are not always available for all countries. Scales: TIMSS: 0-1000, IALS: 0-500, others: 0-100. [a] New Zealand's rank out of participating countries. [b] FS denotes final year of secondary schooling. [c] Third International Mathematics and Science Study. [d] Several countries have a higher upper age limit.

Appendix Table 6: Quality-adjusted measures of human capital

Source	Construction method	Coverage	Top 5 countries	
				Score
			QL1	
			Japan	60.7
			China	59.3
			West Germany	59.0
			Hong Kong	65.9
Hanushek and Kimko (2000)[a]	For **QL1**, data on each of the series are transformed to having a world mean of 50. **QL2** adjusts all scores according to the US international performance modified for the national temporal pattern of scores provided by the National Assessment of Educational Progress. QL1 and QL2 are then constructed by averaging all available transformed test scores, weighted by the normalised inverse of the country-specific standard error for each test.	Including 37 countries participating in at least one international test during 1961-1965, but test scores can be imputed using a regression method for another 49 countries (QL1) or 52 countries (QL2).	Netherlands	56.8
			QL2	
			Singapore	72.1
			Hong Kong	71.9
			New Zealand	67.1
			Japan	65.5
			Norway	64.6

Source	Construction method	Coverage	Top 5 countries
Wößmann (2003)	$h_i^Q = e^{\sum_a r_a Q_i s_{ai}}$ where $r_a =$ world average rate of return to education at level a (20% for primary level, 13.5% for secondary level, 10.7% for higher level) from Psacharopoulos (1994) $Qi =$ QL2 from Hanushek and Kimko (2000) $s_{ai} =$ average years of schooling for population aged 15 and over, from Barro and Lee's (2001) estimates for 1990	151 countries, missing data imputed	Score **New Zealand** 2.47[b] Norway 2.23 Poland 1.67 Hong Kong 1.56 Australia 1.43

Note: [a]The 6 tests used were: IEA Math 1964-1966, IEA Science 1966-1973, IEA Math 1980-1982, IEA Science 1983-1986, IAEP 1988 and IAEP 1991, where IEA refers to the tests administered by the International Association for the Evaluation of Educational Achievement and IAEP to International Assessment of Educational Progress. [b]These figures refer to the country's estimate relative to the US value.

Appendix Table 7: Applicable annual growth rates by year

Future period t in	1981	1986	1991	1996	2001
1-5 years	$g_{1981,1986}$	$g_{1986,1991}$	$g_{1991,1996}$	$g_{1996,2001}$	$g_{1996,2001}$
6-10 years	$g_{1981,1991}$	$g_{1986,1996}$	$g_{1991,2001}$	$g_{1996,2001}$	$g_{1996,2001}$
11-15 years	$g_{1981,1996}$	$g_{1986,2001}$	*	$g_{1996,2001}$	$g_{1996,2001}$
16-20 years	$g_{1981,2001}$	*	*	$g_{1996,2001}$	$g_{1996,2001}$
21+ years	*	*	*	$g_{1996,2001}$	$g_{1996,2001}$

Note: Growth rates vary by ethnic-gender-education-age cohort and are estimated by comparing the current age cohort $a+t$ with the equivalent age cohort $a+t$ in t years. For example, the annual income growth rate in the next 5 years for individuals with ethnic r_i, gender s_i, education e_i, age 21 in 1981 is derived by comparing the average real income of cohort $(r_i, s_i, e_i, 26)$ in 1981 with cohort $(r_i, s_i, e_i, 26)$ in 1986. *Estimated using $g_t = \sqrt[t]{(1+g_{y,2001})^m(1+g_{1996,2001})^{t-m}} - 1$, where y refers to the current year and $m = 2001 - y$.

Appendix Table 8: Descriptive statistics from Census 2001

	Share (%)	Average age	Employment rate (%)[a]	Average income ($)[b]
European				
Male				
Unskilled	14.48	43.0	79.9	34,415
Non-degree	15.71	38.7	86.8	43,276
Bachelors	3.11	39.2	91.2	62,467
Post-graduate	1.60	42.4	92.1	70,138
Female				
Unskilled	15.23	44.5	64.8	22,935
Non-degree	16.30	38.1	75.5	27,889
Bachelors	3.31	35.9	83.4	38,436
Post-graduate	1.43	39.8	85.7	47,100
Sub-total	71.17	40.7	78.2	35,964
Mixed				
Male				
Unskilled	1.15	34.8	71.1	30,148
Non-degree	0.97	31.7	79.7	34,941
Bachelors	0.13	34.2	87.3	48,757
Post-graduate	0.05	38.0	87.4	58,983
Female				
Unskilled	1.40	35.6	53.4	22,394
Non-degree	1.26	30.9	67.6	25,285
Bachelors	0.20	32.2	81.7	34,550
Post-graduate	0.06	36.2	85.4	44,698

	Share	Age	Employment	Income
Sub-total	5.23	33.5	68.3	29,802
Non-European				
Male				
Unskilled	4.93	37.7	61.9	27,289
Non-degree	3.40	34.2	64.5	30,585
Bachelors	0.68	37.4	73.4	44,289
Post-graduate	0.32	40.4	75.1	52,858
Female				
Unskilled	4.98	38.7	45.3	21,684
Non-degree	4.00	34.2	51.9	24,221
Bachelors	0.79	35.5	63.9	32,737
Post-graduate	0.26	37.6	67.0	38,795
Sub-total	19.35	36.6	56.8	27,976
Ethnicity not specified				
Male				
Unskilled	1.97	39.2	12.5	33,442
Non-degree	0.16	38.2	78.4	39,356
Bachelors	0.02	37.1	84.0	48,258
Post-graduate	0.02	41.5	87.8	70,762
Female				
Unskilled	1.93	39.6	7.4	25,004
Non-degree	0.13	39.8	66.9	27,355
Bachelors	0.02	37.1	77.0	36,985
Post-graduate	0.01	41.4	79.7	41,716
Sub-total	4.26	39.3	15.4	33,364

Source: New Zealand Census of Population, 2001.
Note: The population base is ages 18-64. [a]Share of the population who were working for an income. [b]Average income of paid employees.

Appendix Table 9: Descriptive statistics from the IALS

Variable	Mean	Std. Dev.	Mean	Std. Dev.
	Canada (N=2452)		*United States* (N=1722)	
Age	37.6	11.2	39.8	11.6
Years of schooling	13.1	3.5	13.8	3.1
Prose score	290	60	288	61
Document score	293	63	282	64
Numeracy score	294	59	289	63
Weeks worked	44.2	14.6	46.8	12.8
Earnings	26,752	22,155	27,951	25,422

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Proportions who are:				
Male	.57		.5	
Rural	.17		.74	
Migrant	.18		.13	
Native speaker	.95		.93	
Employed	.98		.97	
Part-time	.17		.16	
	Poland (N=1536)		*Sweden* (N=1830)	
Age	38.5	10.2	40.1	12.4
Years of schooling	11.7	2.9	11.9	3.5
Prose score	237	54	306	46
Document score	235	65	310	47
Numeracy score	247	64	311	48
Weeks worked	47.1	12.7	43.8	16
Earnings$^{\$}$	45,739	46,580	152,641	92,245
Proportions who are:				
Male	.56		.52	
Rural	.32		.32	
Migrant	.01		.07	
Native speaker	1		.93	
Employed	.97		.95	
Part-time	.07		.18	
	Ireland (N=1682)		*United Kingdom* (N=4029)	
Age	37	12.6	38.6	11.6
Years of schooling	10.6	3.1	12.5	2.7
Prose score	268	55	281	50
Document score	263	57	284	55
Numeracy score	269	61	284	55
Weeks worked	34.2	23.1	49	9.3
Earnings$^{\#}$	9,035	8,571	13,586	7,552
Proportions who are:				
Male	.56		.55	
Rural	.39		.23	
Migrant	.06		.07	
Native speaker	.99		.99	
Employed	.73		1	
Part-time	.13		.23	
	Netherlands (N=1856)		*Switzerland* (N=1560)	
Age	37.1	10.9	38.7	12.1

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Years of schooling	13.3	4	12.5	3.2
Prose score	290	40	271	49
Document score	295	41	279	56
Numeracy score	296	43	287	50
Weeks worked	44.9	16	46.5	13.8
Earnings[#$]	44,274	33,688	51,360	32,600
Proportions who are:				
Male	.58		.54	
Rural	.2		.26	
Migrant	.06		.16	
Native speaker	.95		.94	
Employed	.93		.95	
Part-time	.23		.2	
	Belgium (N=1048)		*Germany* (N=1125)	
Age	37.5	10.2	39.8	12.4
Years of schooling	12.6	3.1	11.6	3.3
Prose score	279	51	278	45
Document score	287	49	289	44
Numeracy score	292	55	296	42
Weeks worked	47.5	13.1	44.6	17.2
Earnings[#†$]	34,801	12,903	2,395	1,930
Proportions who are:				
Male	.59		.58	
Rural	.27		.43	
Migrant	.03		.07	
Native speaker	.98		.96	
Employed	.96		.88	
Part-time	.2		.18	
	New Zealand (N=2400)			
Age	37.5	11.9		
Years of schooling	12.3	2.8		
Prose score	286	51		
Document score	281	52		
Numeracy score	283	51		
Weeks worked	44.8	14.1		
Earnings[#]	26,779	21,879		
Proportions who are:				
Male	.52			
Rural	.24			
Migrant	.18			

Variable	Mean	Std. Dev.	Mean	Std. Dev.
Native speaker	.96			
Employed	1			
Part-time	.28			

Source: The International Adult Literacy Survey.
Note: Evaluation of literacy is based on a continuous scale from 0 to 500. *Native speaker* = 1 if the respondent's best language is a major, official language of his country of residence; in New Zealand this language is English. *Employed, Earnings, Part-time, Weeks worked* refer to jobs held in the past 12 months; *Earnings, Part-time, Weeks worked* = 0 if *Employed* = 0. *Earnings* are in local currency and are continuous, annual and before taxes, unless otherwise noted. #Calculated from midpoints of intervals. †Monthly. $After taxes and other payroll reductions. All estimates are weighted. The sample is restricted to ages 18-64.

Appendix Table 10: Contribution of each latent variable in explaining literacy skills and human capital

	Path coefficient	Correlation	% contrib. to R^2
Belgium			
Literacy skills ($R^2 = 0.36$)			
Parental education	0.06	0.28	5.0
Educational achievement	0.45	0.52	65.2
Age	0.37	-0.20	-21.0
Age squared	-0.50	-0.22	30.4
Male	-0.01	-0.04	0.1
Migrant	-0.13	-0.25	9.2
Native speaker	0.14	0.28	11.1
Rural	0.00	0.04	0.0
Human capital ($R^2 = 0.29$)			
Parental education	0.00	0.02	0.0
Educational achievement	0.23	0.25	19.8
Age	1.17	0.20	80.2
Age squared	-0.96	0.17	-57.9
Male	0.40	0.40	55.0
Migrant	0.01	-0.02	-0.1
Native speaker	-0.03	0.00	-0.0
Rural	-0.02	0.03	-0.2
Literacy skills	0.07	0.14	3.5
Canada			
Literacy skills ($R^2 = 0.45$)			
Parental education	0.19	0.42	18.0
Educational achievement	0.53	0.62	73.7
Age	0.17	-0.21	-7.6
Age squared	-0.22	-0.22	10.9

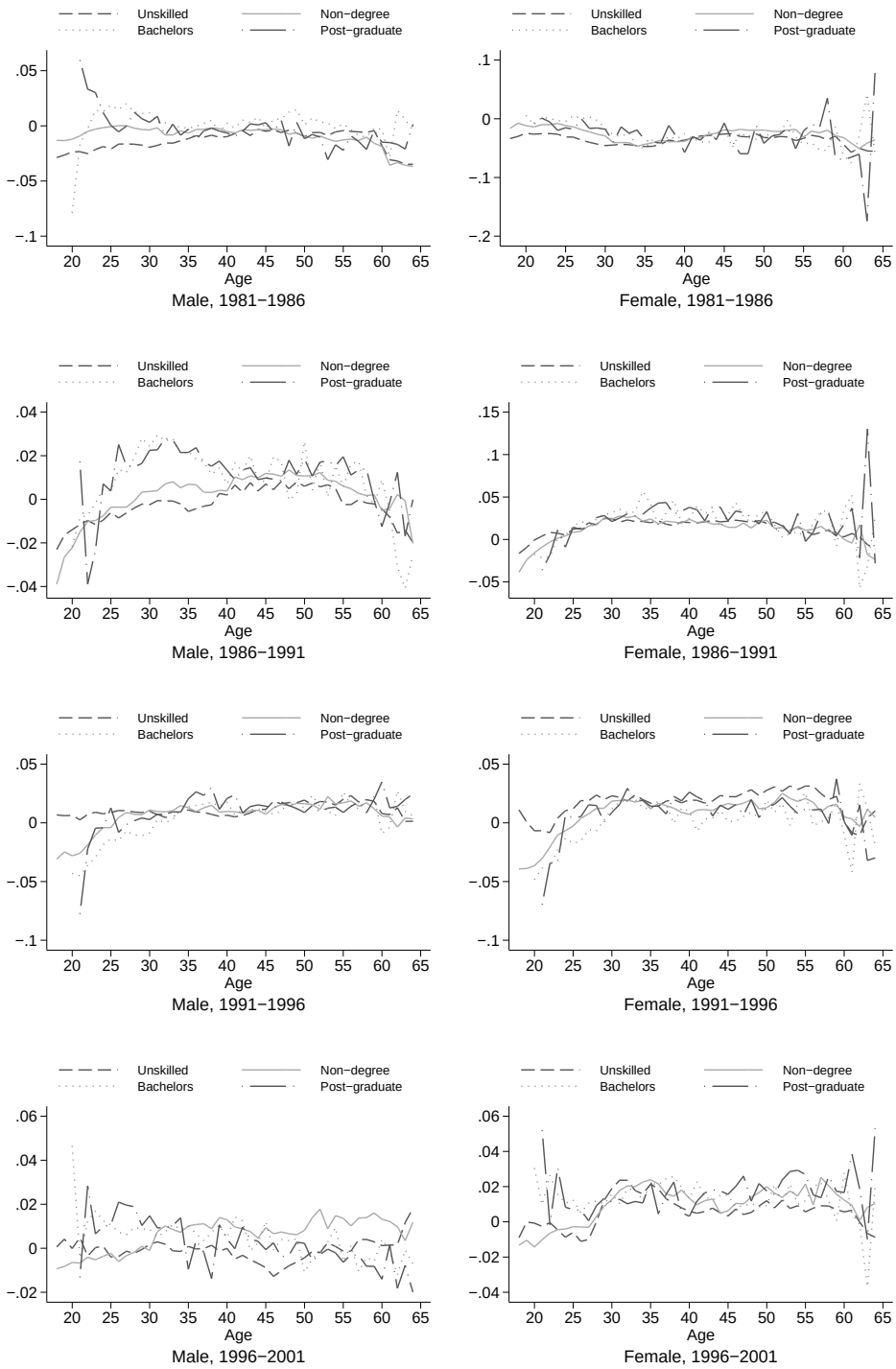
	Path coefficient	Correlation	% contrib. to R^2
Male	-0.03	-0.09	0.7
Migrant	-0.05	-0.04	0.5
Native speaker	0.10	0.18	4.1
Rural	0.01	-0.10	-0.2
Human capital ($R^2 = 0.29$)			
Parental education	0.02	0.01	0.1
Educational achievement	0.19	0.23	15.4
Age	1.68	0.30	174.7
Age squared	-1.34	0.25	-119.1
Male	0.25	0.22	19.2
Migrant	0.00	0.05	0.0
Native speaker	-0.02	0.01	-0.1
Rural	-0.07	-0.10	2.6
Literacy skills	0.12	0.17	7.2
Germany			
Literacy skills ($R^2 = 0.19$)			
Parental education	0.12	0.19	11.4
Educational achievement	0.28	0.35	49.9
Age	0.45	-0.15	-35.2
Age squared	-0.56	-0.16	47.7
Male	0.04	0.05	1.1
Migrant	-0.14	-0.19	14.3
Native speaker	0.08	0.17	7.4
Rural	-0.07	-0.09	3.4
Human capital ($R^2 = 0.29$)			
Parental education	0.04	0.02	0.3
Educational achievement	0.08	0.18	5.3
Age	2.34	-0.17	-134.8
Age squared	-2.51	-0.22	192.0
Male	0.28	0.27	26.6
Migrant	-0.08	-0.09	2.5
Native speaker	-0.01	0.06	-0.3
Rural	0.00	0.01	0.0
Literacy skills	0.12	0.22	8.8
Ireland			
Literacy skills ($R^2 = 0.32$)			
Parental education	0.09	0.33	8.8
Educational achievement	0.47	0.54	79.4
Age	0.48	-0.22	-33.4
Age squared	-0.56	-0.24	40.9

	Path coefficient	Correlation	% contrib. to R^2
Male	0.03	-0.00	-0.0
Migrant	-0.01	0.03	-0.1
Native speaker	-0.03	-0.07	0.6
Rural	-0.08	-0.14	3.6
Human capital ($R^2 = 0.27$)			
Parental education	0.06	0.21	4.5
Educational achievement	0.23	0.35	29.2
Age	1.29	-0.04	-18.2
Age squared	-1.24	-0.07	32.0
Male	0.25	0.24	21.5
Migrant	-0.05	-0.02	0.3
Native speaker	0.01	-0.02	-0.0
Rural	0.00	-0.05	-0.1
Literacy skills	0.23	0.37	30.7
Netherlands			
Literacy skills ($R^2 = 0.27$)			
Parental education	0.17	0.31	19.5
Educational achievement	0.34	0.42	52.1
Age	0.37	-0.23	-30.7
Age squared	-0.52	-0.24	45.6
Male	0.01	0.01	0.1
Migrant	-0.13	-0.17	8.1
Native speaker	0.07	0.14	3.5
Rural	-0.06	-0.08	1.7
Human capital ($R^2 = 0.35$)			
Parental education	0.05	0.01	0.1
Educational achievement	0.09	0.18	4.8
Age	0.95	0.20	52.8
Age squared	-0.76	0.18	-37.9
Male	0.50	0.53	75.4
Migrant	0.01	-0.02	-0.1
Native speaker	0.01	0.02	0.0
Rural	0.02	0.02	0.1
Literacy skills	0.12	0.14	4.6
Poland			
Literacy skills ($R^2 = 0.29$)			
Parental education	0.09	0.30	9.2
Educational achievement	0.44	0.51	77.3
Age	0.08	-0.19	-5.4
Age squared	-0.18	-0.20	12.6

	Path coefficient	Correlation	% contrib. to R^2
Male	0.00	-0.02	-0.0
Migrant	-0.03	-0.04	0.5
Rural	-0.08	-0.23	5.9
Human capital ($R^2 = 0.13$)			
Parental education	0.04	0.06	1.7
Educational achievement	0.19	0.20	29.0
Age	1.74	0.07	90.3
Age squared	-1.65	0.03	-37.2
Male	0.16	0.12	15.3
Migrant	-0.01	-0.01	0.1
Rural	-0.02	-0.09	1.6
Literacy skills	-0.03	0.08	-1.8
Switzerland			
Literacy skills ($R^2 = 0.34$)			
Parental education	0.08	0.31	7.3
Educational achievement	0.39	0.47	54.8
Age	-0.04	-0.18	2.0
Age squared	-0.05	-0.18	2.9
Male	0.00	0.06	0.1
Migrant	-0.27	-0.37	29.6
Native speaker	0.08	0.16	3.5
Rural	-0.00	0.01	-0.0
Human capital ($R^2 = 0.31$)			
Parental education	0.01	0.07	0.1
Educational achievement	0.12	0.24	9.0
Age	0.94	0.15	44.0
Age squared	-0.80	0.13	-33.0
Male	0.47	0.50	74.4
Migrant	-0.03	-0.06	0.6
Native speaker	-0.00	-0.00	0.0
Rural	-0.04	-0.04	0.5
Literacy skills	0.09	0.16	4.4
United Kingdom			
Literacy skills ($R^2 = 0.25$)			
Parental education	0.14	0.29	16.0
Educational achievement	0.34	0.42	57.4
Age	0.23	-0.20	-18.9
Age squared	-0.32	-0.21	27.2
Male	0.06	0.05	1.2
Migrant	-0.11	-0.21	9.4

	Path coefficient	Correlation	% contrib. to R^2
Native speaker	0.10	0.20	7.8
Rural	0.02	-0.03	-0.2
Human capital ($R^2 = 0.30$)			
Parental education	0.01	0.12	0.6
Educational achievement	0.06	0.09	1.6
Age	2.70	0.30	270.8
Age squared	-2.40	0.24	-195.1
Male	0.24	0.24	19.3
Migrant	-0.05	-0.03	0.5
Native speaker	0.00	0.03	0.1
Rural	-0.07	-0.06	1.4
Literacy skills	0.06	0.07	1.3
United States			
Literacy skills ($R^2 = 0.54$)			
Parental education	0.16	0.43	12.6
Educational achievement	0.47	0.61	53.4
Age	0.32	-0.05	-2.9
Age squared	-0.34	-0.06	3.8
Male	-0.03	-0.03	0.1
Migrant	-0.24	-0.45	19.7
Native speaker	0.17	0.43	13.1
Rural	-0.00	-0.04	0.0
Human capital ($R^2 = 0.28$)			
Parental education	0.04	0.14	1.9
Educational achievement	0.18	0.32	20.9
Age	1.73	0.19	116.4
Age squared	-1.54	0.15	-80.4
Male	0.26	0.26	24.1
Migrant	0.05	-0.05	-0.7
Native speaker	-0.01	0.07	-0.3
Rural	-0.02	-0.01	0.1
Literacy skills	0.18	0.28	17.8

Appendix Figure 1: Growth rates in real annual income



Source: New Zealand Censuses of Population 1981, 1986, 1991, 1996, 2001.