Technical Change & Wages in Australia

Alex Cooper

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Abstract

Could technology be responsible for part of the rise in income inequality over the past 30 years? This research is motivated by the fact that, while technology can make workers more productive, it can also render other workers unneccessary by automating some tasks. By changing demand patterns for different kinds of labor, it is possible that technology is responsible for an increase in the demand and wage of certain types of work, and a reduction in the wage and number of others. Research from the United States and Europe suggests that technological change has indeed caused such a 'polarization' of the wage distribution.

In this thesis, we assess the evidence for polarization in Australia. We first consider the standard model of skill-biased technical change, and show that it only poorly fits the observed data. We link the wage share of middle-skilled occupations to investment in electronic and electrical capital goods, and also demonstrate a relationship between qualitative properties of certain jobs, and changes in the wage distribution. We find that jobs of the kind most likely to be impacted by technology, so-called 'routine' jobs, have suffered the greatest decline in income over the past 30 years, and that the penalty associated with routine work is concentrated in upper wage quantiles. Finally, we find a large change in the value of occupations involving managerial tasks, an effect that may or may not be associated with technical change.

Contents

Chapter 1

Introduction and Motivation

The second half of the 20th century has witnessed tremendous change for Australian workers. To a great extent, these changes reflect the beneficial effect of economic growth: since 1973, average real per capita incomes have approximately doubled, and economic growth has added over three million jobs to the work force (ABS, 2013a, 2013b). Yet, even as mean incomes have increased and the work force expanded, these benefits have been unevenly spread. This period bore witness to a dramatic change in the distribution of incomes: Australia, like many developed countries, became less equal. Over the four decades following the Second World War, the gap between high and low income earners fell, but began a sharp rise from the 1980s onward, a period that Leigh (2013) calls the 'Great Divergence.' During this time, top percentile wage earners saw their incomes increase dramatically, whereas some groups of workers did not see much income growth at all (Atkinson, 1997; Borland, 1999; Leigh, 2013).

The motivation for studying the changing determinants of income is perhaps obvious. To the extent that an individual's welfare is determined by the resources at his or her disposal, understanding those factors that drive changes in the level and distribution of wealth is an important role for the social sciences. To properly analyze wealth inequality, the determinants of household income flows need to be understood. However, the sheer diversity of these flows complicates this task. Household wealth can be accumulated from many sources: wages from labor, dividends from financial investments, government entitlements, other lump-sum cash transfers, capital gains on assets, and so on. The scope of this study is limited to just one of these flows: wages from labor income. Indeed, wages are the principal source of income for the majority of Australian households. Thus, any changes to the distribution of labor income are likely to have a significant impact on households' welfare.

A somewhat less obvious application for models of occupational wages applies to education policy and occupational choice. Young people must choose an educational path to equip them for a career, but there is some degree of uncertainty about the present value of a given career choice in the presence of technical change (see e.g. Dixit, 1994, ch. 12). The neoclassical model of human capital outlined by Becker (2009) tells us that individuals make education investment decisions based on the rate of return of the career that education enables. However, without a good knowledge of the returns that occupations will yield over the coming decades, individuals are not in a position to evaluate the present value of any education investment. Clearly, a better understanding of the determinants of the occupational wage profiles is valuable to policymakers and prospective workers alike.

By focusing on individuals' wages, as the flow of labor income, we limit our ability to make direct inferences about welfare. Social welfare, as a function of income, is best considered at the household level, since income and housing costs are typically pooled between household members, and individuals do not spend their entire lives earning income (Richardson & Harding, 1999; Borland, 1999). Children and retirees who are not working, for example, are not directly affected by changes in the distribution of wage income, but they may experience indirect effects through the earnings of the family breadwinners. Further, because households may have multiple wage earners, evidence of growing wage inequality may not translate directly into income inequality between households. Richardson and Harding (1999) provide evidence that individuals earning very low incomes are more likely to work part-time, as a secondary source of household income. Indeed, individuals may actually prefer to accept low-wage, part-time work, rather than higher-paid work that carries a greater time burden. Notwithstanding these limitations, in this study we consider changes in the distribution of income earned as an employee.

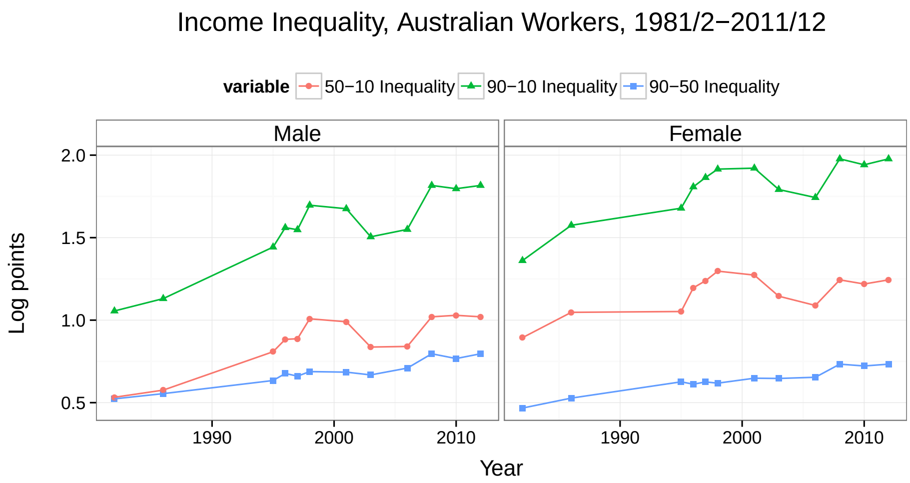

Figure 1.1: Change in income inequality measures for Australian workers, 1981/82 to 2011/12. The three measures refer to the differences between deciles of the log wage distribution. Unlike subsequent chapters of this study, which considers only full-time workers, these calculations include part-time as well as full-time employees, and workers of own account. Working populations are composition adjusted according to four educational attainment levels and five age categories. All calculations are weighted by survey weight. Source: ABS cat. 6543.0, 6541.0, 6503.0.

Understood as the dispersion of wage income earned by Australian workers, income inequality has grown over the period of the 'Great Divergence' in Australia. Figure 1.1 illustrates three measures of wage inequality, computed as the gap between quantiles of the log earnings distribution. *90-10 inequality*, the difference between the 90th and 10th quantiles, summarizes the overall spread of the earnings distribution. *90-50* and *50-10 inequality* respectively describe the extent of the upper and lower 'tails' of the distribution, relative to the median. Over the 30 years since the 1981/82 fiscal year and 2011/12, 90-10 inequality grew from 1.1 to 1.8 log points for males, and from 1.3 to 2.0 log points for females. In percentage terms, the income gap between men earning at the 90th percentile has grown from about 200% of incomes of men in the 10th percentile, to about 300% in 2011/12. For women, this figure has grown from 267% to 639%.

The causes of this rapid increase in income inequality in Australia have been the subject of some debate, and it is unlikely to be the outcome of any single change of labor market conditions. Leigh (2013) names three principal causes for this surge in income inequality in Australia: falling union rates, falling income taxes and skill-biased technology.

The relationship between the rate of union membership and inequality has been well-established (see, *inter alia*, Borland, 1996). Unions tend to reduce income inequality in the bottom of the income distribution, because they tend to bargain for across-the-board wage agreements rather than individually-negotiated employment contracts, resulting in a 'compression' of the income distribution. Unions have also argued for limitations on top executive pay (E. Davis, 2009). Any reduction in the rate of union membership therefore limits the degree of wage compression, so magnifying income inequality. This effect has been well studied elsewhere: empirical studies in the US, UK and Canada have found a significantly negative union effect on inequality (Card, Lemieux, & Riddell, 2004; Firpo, Fortin, & Lemieux, 2009).

The second major cause for the Great Divergence is falling income taxation rates. The top marginal income tax rate in the 1980s was around 60 per cent, but this has fallen to around 40 per cent today. Consequently, the average tax rate paid by wealthy Australians has fallen, resulting in a greater divergence of accumulated wealth across the population (Leigh, 2013, p.31). Atkinson and Leigh (2013) estimate that about one third of the increase in inequality in top incomes is due to decreases in income tax.

But by far the greatest driver of increasing inequality is the inexorable rise in workplace technology. In particular, new computer and information technologies complement the activities of skilled workers, making them much more productive, but leaving unskilled workers' productivity largely unchanged. Under this model of so-called 'skill biased technical change' (SBTC), new workplace technologies disproportionately complement highly-skilled technical and managerial labor (Griliches, 1969; Autor, L. F. Katz, & Kearney, 2006). As a result of higher productivity, wages for high-skilled jobs increase, with demand for workers outstripping the supply. Likewise, as the relative demand for lower-skilled workers has softened, so relative wage growth has stagnated.

The three phenomena outlined above may not operate independently. Acemoglu (2003) analyze a model where skill-biased technology reduces the incentives for workers to accept the trade-off between lower wages and the improved job security and bargaining services that unions offer. If skill-biased technology improves the earnings capacity for workers with higher levels of talent or human capital, then the opportunity cost of giving up individually-negotiated contracts (where earnings may depend on that individual's above-average level of productivity) is considerably higher. It is thus possible that unions 'amplify' inequality caused by skill-biased technical change.

The surge in inequality over the past 30 years is not a uniquely Australian experience. Atkinson and Leigh (2013) analyze top income rates from five Anglo-Saxon countries' tax data, and find that Australian trends described above correspond closely to the inequality patterns seen in the US, UK, Canada and New Zealand, on a wide variety of inequality measures. In all five countries, the income share accruing to the richest 0.1 per cent of income earners fell over the middle part of the twentieth century. In 1920, this group received between four and six per cent of national income (eight per cent in the UK), a figure that was to fall over the following half century to a nadir of around two per cent in 1980. Since the 1980s, the so-called Great Divergence has been experienced by all five countries.

Of the many drivers of inequality, this thesis will focus on just one: the rise of skill-biased technology, and the impact of its adoption by firms. The SBTC argument, which has sparked a voluminous literature, has enjoyed considerable empirical success explaining rising wages for high-skilled managerial and professional jobs in the United States and Europe (Katz & Murphy, 1992). Since the canonical model includes *factor-augmenting* capital, it predicts monotonic skill upgrading of the work force at all education levels (Autor, Levy, & Murnane, 2003). Skill upgrading has been confirmed by a number of authors, both in Australia (Esposto, 2012; Wooden, 2000; Cully, 1999) and overseas (Autor, L. F. Katz, & Kearney, 2008).

There are good reasons for focusing on technology as a driver of changes in the work force. Although mechanical computers and computation aids (the abacus, for instance), have been available for centuries, it was only in the post-war era, with the arrival of electronic computation, that the price of computation began to fall dramatically. Nordhaus (2007) estimates that, between 1946 and 2006, the cost per computation decreased by a factor of *seven trillion,* and over the same period, the cost of data storage fell at a comparable rate. The falling cost of computation opened up new avenues for research in information technology, so that even as computation became cheaper, new and improved algorithms were developed which made more efficient use of, and found novel uses for, computing power. And as computers have become cheaper and more useful, firms have made greater use of them. Between 1981 and 2012, Australian firms' real annual investment in computers has grown from $26M to $14B, in constant 2012 dollars (ABS, 2013a).

The canonical model also predicts a rising premium for high-skilled workers. In the United States in particular, SBTC has been able to explain the dynamics of the wage premium demanded by tertiary-educated labor, which fell in the 1970s and has risen in the decades to 2008 (Acemoglu & Autor, 2011). However, the model substantially *over-predicts* the magnitude of this differential for the United States (Autor, L. F. Katz, & Kearney, 2008). In Australia, a corresponding growth in the premium for tertiary qualifications has not been observed (Coelli & Wilkins, 2009).

In addition to the lack of an observed skill premium in Australia, evidence from foreign labor markets suggests that there are a number of empirical regularities that the canonical model fails to explain. Since the late 1990s, both in Europe and the United States, the data show a marked polarization in the work force (Goos & Manning, 2007; Autor, L. F. Katz, & Kearney, 2006). This polarization has simultaneously manifested in *wages* and in *jobs*: both wage growth and growth in the level of employment are concentrated in high-skilled jobs, and to a lesser extent, the bottom end of the skill spectrum. Middle-skilled jobs have stagnated since the 1990s, both in terms of remuneration and level.

The rise of inequality in Australia has been well documented. Empirical studies have confirmed that both individual-level and household-level inequality have been rising since the 1980s (Borland, 1999; Leigh, 2005, 2013; Gaston & Rajaguru, 2009). A number of studies exist on the task content of Australian jobs (Esposto & Garing, 2012), and the change over time of the skill intensity of various professions (Esposto, 2012; Esposto & Garing, 2012). Although ICT use and globalization have been found to Granger (non-)cause rising inequality at the aggregate level (Gaston & Rajaguru, 2009), no studies have tested whether workers' job types and on-the-job activities explain the nature of these changes.

The empirical goals of this research are structured according to three related, but separate lines of inquiry. First, we review the empirical evidence for skill-biased technical change, and produce estimates of the skill premium for recently-released data. Second, we extend our analysis to consider whether the impact of SBTC is polarizing, rather than simply widening, the income distribution. And finally, we seek to quantify the channels by which changes in the income distribution have occurred, by decomposing changes in the income distribution into the tasks that comprise occupations. Finally, we review and suggest avenues for further research.

Chapter 2

Theoretical Literature

Advances in technology are responsible for much of the rapid growth in incomes over the course of human history. From advances in metallurgy millenia ago to the relatively recent development of mobile telephony, technological change is disruptive: it creates winners, but it also creates losers as investments in yesterday's technology are rendered obsolete.

This chapter reviews the literature on technical change, as it relates to workers' wages in the face of recent technical change. We stay mostly within the bounds of the neoclassical school. We begin with growth models, that consider technology as a uniform force upon all parts of the labor force. We then discuss models for skill-biased change, and in particular the 'canonical model.' Next, we consider the 'task approach', which adapts the neoclassical model to allow for competition between human workers and capital. Finally, we discuss the Roy model and 'Ricardian' models of the labor market.

2.1 Early Treatments of 'Technology'

Most early treatments of technical change in the economic literature assume 'technology' has a uniform impact across all types of production. For example, Ricardo (1819) considers two types of innovations: landsaving innovations, that increase the output of every grade of land equiproportionally, and capital-and-labor saving innovations, that scale the output of capital and labor inputs evenly across the economy.

More recent examples of technology that act across the whole economy are found in the growth accounting literature. Consider, for example, the neoclassical model of growth, that views production through the lens of the neoclassical production function, a kind of black-box function that 'converts' inputs of capital and labor into an output good. Most formulations of the production function include a 'productivity' parameter, that governs the rate at which factors of production are converted into outputs. Solow's (1957) well-known functional form,

$$F(K, L, t) = A(t)f(K, L), \tag{2.1}$$

included measures for capital (K) and labor (L) inputs, but also allowed 'technology' ($A(t)$), which he called total factor productivity (TFP), to vary over time. He deliberately left the definition of TFP vague, to simply mean any change in the rate of production: "all sorts of things will appear as technical change" (Solow, 1957, p.312). TFP, then, was whatever was not already accounted for by measured capital and labor.

To estimate TFP, Solow (1957) rearranged (2.1) and substituted US national accounting statistics from 1909 to 1949 for real GDP, capital and labor. The resulting estimates of TFP increased more or less monotonically over the first half of the 20th century, and by 1949 A had grown to about double its initial value.

Today, the neoclassical approach to growth accounting remains an important field of study for understanding the interaction of 'technology' and income. Mankiw, Romer, and Weil (1992), for example, demonstrated that, a Solow model augmented to include a measure of human capital as a factor of production, can explain cross-country variation in the level of income very well indeed. However, as elegant and convenient as the neoclassical growth model is, and notwithstanding its success at explaining the dispersion of incomes between countries, it does not explain the evolution of wage profiles within countries. In particular, it has not been able to explain the secular trend of increasing income inequality over the past 30 years in developed countries.

2.2 Rising US Education Premia

For much of the 20th century, wage growth differentials between different skill and educational groups in the United States had remained more or less stable. However, beginning in the 1980s, empirical evidence showed that the wages of skilled workers had begun to grow faster than those of unskilled workers (Juhn, Murphy, & Pierce, 1993). At the same time, the supply of skilled workers in the United States, relative to unskilled workers, had grown dramatically. These empirical regularities suggested that, since firms were demanding increasing amounts of high-skilled labor, even at increasing wage rates, the productivity of skilled workers had increased, relative to that of unskilled workers. The existing neoclassical model could shed no light onto this trend, and a more nuanced understanding of the relationship between technology and productivity was required.

One set of explanations pointed to the changing nature of labor market institutions. Freeman (1994), for example, suggested that about 50 per cent of the increase in the 'white collar' premium paid to US men could be explained by the decline in the unionization rate. If it is accepted that union bargaining activities result in a narrowing of wage dispersion between unionized workers, then a decrease in the union rate should result in a loss of worker bargaining power, and thus a decrease in wages. But since unions tend to cover mainly 'blue-collar' occupations, then this trend should result in a widening gap between blue- and white-collar work. Indeed, recent studies of the relationship between the union membership rate and the dispersion of income lend this explanation solid empirical support, both in the United States (Card, Lemieux, & Riddell, 2004; DiNardo, Fortin, & Lemieux, 1996) and Australia (Borland, 1996).

Other institutional explanations for the growing premium paid to skilled workers include sociological changes, such as changes in norms associated with worker pay (Mitchell, 1989). Another quite plausible explanation for the observed trends, is completely independent of any qualitative change in the nature of technology or jobs. According to this view, the rise in the relative demand for skilled labor, and concomitant decline in the density of union workers, simply reflected broader economic trends, as changes in the composition and distribution of production activity.

One economic trend that could bring about a change in the demand for skilled and unskilled labor is the transfer of many US manufacturing jobs overseas. This argument was advanced by Murphy and Welch (1992), who appeal to changes in the demand structure of US labor as a consequence of trade and competition with overseas producers. The patterns of US trade shifted over the 1980s from trade surplus to deficits, favoring the manufacture of goods in low-cost countries, instead of with domestic, high-cost workers. Murphy *et al.* study the relationship between wage rates for white males between 1963 and 1979, and macroeconomic measures of output and wages both in the US and overseas, concluding that changing patterns of trade go a long way to explain changes in the wage structure.

During this debate, some authors argued that technological progress might have reduced demand for certain kinds of physical work by enabling the substitution of capital for labor. Using longitudinal data gathered from census files, S. J. Davis and Haltiwanger (1991) argue that, through capital investment in automated equipment and machinery, the manufacturing sector replaced labor-intensive jobs with plant capital. Under this explanation, growing wage differentials between college-educated workers and high school graduates is a result of changes in the demand for labor, as the demand for non-manual work increases, and the demand for manual labor softens. Krueger (1993) expanded on this argument: using microdata on individual workers, he found a premium associated with those occupations that involve computer use.[1] Kreuger's observation that wage changes are due to the *nature* of the work (the fact that computers are used), rather than its outputs or the skills required to undertake it, was to become an important consideration in future work.

2.3 Models of Skill-Biased Technical Change

The explanation for rising skill premia that won acceptance in the literature is that new technologies, emerging over the post-war era, are complementary to skilled work, but not other types of labor. Based on US manufacturing data, Griliches (1969) proposed models of labor-augmenting technology, which he called 'capital-skill complementarity.' The modern form of the 'canonical' SBTC model is due to Tinbergen (1974, 1975), who developed

[1] For a rather sardonic refutation of Krueger's position, see DiNardo and Pischke (1997), who show that an effect of a similar magnitude is associated with occupations that employ the use of lead pencils.

a model of the labor market where different kinds of labor were factors in production. His model, which included university graduates and unskilled workers, employed the familiar CES production function of the form,

$$F(L_1, L_2) = \left[\alpha(\beta_1 L_1)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\beta_2 L_2)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{2.2}$$

but allowed each type of labor to have different levels of efficiency, β_i.

Naturally, models of the division of labor are not new: since the time of Adam Smith, it has been well known that the productivity of modern production processes, at any scale, depends crucially on the specialization of labor into a number of different jobs. In Adam Smith's famous study of a pin factory, Smith observed somewhere between a 240– and 4800–factor increase because of complementarities between different, specialized jobs (Smith, 1776, p. I.3). Tinbergen recognized that it would be unwieldy to attempt to model every type of job using a production function, as the dimensionality of the model would quickly explode. However, armed with the observation that many properties of jobs are highly correlated, he proposed that a good characterization of the labor market can be made by singling out just one or two properties of different jobs. One particularly relevant property of jobs is the degree of *schooling* an individual has received. Tinbergen (1974) modeled graduate and unskilled workers as imperfect substitutes in production, to capture the fact that firms typically have to hire different types of workers—and so that changes in the productivity of one type of labor affects demand for *all* types of labor.

Tinbergen identified two implications of his model. First, since the higher-productivity 'graduate' workers were scarce relative to the supply of unskilled workers, graduates would be able to charge employers 'scarcity rents,' as well as additional rents for their individual productivity. In the medium run, the availability of these rents would induce a 'race' for investment in education, as unskilled workers seek to increase their human capital in order to access these rents.

Tinbergen's model was further developed by Katz and Murphy (1992) and others, and brought to bear on the empirical regularity of rising educational returns in the United States and elsewhere, beginning in the 1980s. In their model, they suggest that new workplace technologies disproportionately complement highly-skilled technical and managerial jobs, relative to low-skilled manual and service jobs. Under this explanation, the premium paid to high-skilled labor increases for two reasons: first, since high-skilled workers become relatively more productive, wages to high-skilled occupations are higher at the margin. There is also evidence that, in the United States at least, an increase in the demand for skilled labor, relative to its supply, has resulted in higher wages for skilled occupations. Such technologies are said to exhibit *skill bias* (Autor, L. F. Katz, & Kearney, 2006).

In addition to the rising skill premium, and the observation that it was high-skilled workers that benefited from the new computing and telecommunications technology appearing in the 1980s, there was 'virtually unanimous agreement' that SBTC was responsible for the increase in demand for high-skilled workers (Johnson, 1997, p.41). A wealth of empirical evidence was accumulated, at the industry and country level (Berman, Bound, & Griliches, 1994; Autor, L. F. Katz, & Krueger, 1998; Berman, Bound, & Machin, 1998), and at the firm and plant level (Levy & Murnane, 1996; Bresnahan, Brynjolfsson, & Hitt, 2002). However, there nonetheless remained dissenting voices, which we briefly review below (§2.5).

2.4 The Canonical Model

The formulation of the SBTC model that gained wide acceptance in the literature, dubbed the 'canonical model' by Acemoglu and Autor (2011), was adopted by a large number of authors analyzing skill-biased technology (e.g. Katz & Murphy, 1992; L. F. Katz & David, 1999; Goldin & L. F. Katz, 2007; Acemoglu & Autor, 2011). We will briefly outline the main features and implications of this model, following the notation employed by Acemoglu and Autor (2011).

The canonical model imagines an economy where the only inputs to production are two types of workers, those with 'high' skill and those with 'low' skill, that work together to produce a single output good. These two types of workers are imperfect substitutes, so that although firms require both types of workers, they will select the mix of labor they demand based on their relative efficiency. Both types of workers employ a generic 'technology', similar to Solow's TFP, represented by a single number. This number linearly scales their output, and determines how efficient their labor is. Although this isn't important for the main findings, the model is flexible enough to consider variety within the workforce. Workers are paid according to how much they individually contribute to production, and each individual has a different level of productivity. We can then think about the total amount of productive effort contributed by both types of labor as our inputs to production.

Formally, consider a competitive economy with two different, imperfectly substitutable types of labor: high-skilled and low-skilled. Workers are heterogeneous, with different levels of efficiency within each skill group. Denote the efficiency distribution of workers in the high- and low-skilled groups $\mathcal{H}$ and $\mathcal{L}$, respectively, so that worker i supplies $h_i \in \mathcal{H}$ efficiency units, and worker j in the low-skilled group supplies $\ell_j \in \mathcal{L}$. Let the total supply of each type of labor be H, and L, respectively, where

$$H = \int_{h_i \in \mathcal{H}} h_i \; di \quad \text{and} \quad L = \int_{\ell_j \in \mathcal{L}} \ell_j \; dj,$$

and both types are paid the same wage per efficiency unit, respectively w_h and w_ℓ. Production in this economy is governed by a constant elasticity of supply (CES) aggregate production function,

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{1}{\sigma-1}}, \tag{2.3}$$

where the elasticity of substitution is $\sigma > 1$, and the coefficients A_L and A_H represent the 'technology' that governs the efficiency of each type of worker. Below, we will alter these parameters to conduct experiments on the impact of technological change on wage levels.

For our purposes, we are interested in two claims about relative wages made by this model: that neither technological improvements, nor a generalized shift from low-skilled to high-skilled work should ever cause low-skilled wages to decrease, and that SBTC should result in a monotonic increase in wages across the skill spectrum. To see this, we will first derive the expressions for the equilibrium wage for each type of labor. Since the economy is competitive, unique equilibrium wages for both both high- and low-skilled workers are given by their respective marginal products. Wages can therefore be found by differentiating (2.3) with respect to labor supply:

$$w_h = \frac{\partial Y}{\partial H} = A_H^{\frac{\sigma-1}{\sigma}} \left(A_L^{\frac{\sigma-1}{\sigma}} (H/L)^{-\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} \tag{2.4}$$

$$w_l = \frac{\partial Y}{\partial L} = A_L^{\frac{\sigma-1}{\sigma}} \left(A_L^{\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}} (H/L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} \tag{2.5}$$

The first claim follows from differentiating these wage equations. Notice in (2.5) that $\partial w_l/\partial A_H \geq 0$. This means that, in this model, an increase in technology for high-skilled workers does not reduce the wage for low-skilled workers. Technological progress should in fact result in positive wage improvements for both high- and low-skilled workers.

Next, it can be shown that $\partial w_l/\partial(H/L) > 0$. An increase in the relative supply of high-skilled workers, H/L, should therefore not decrease the wage of low-skilled workers. Rather, as high-skilled work becomes more productive and the ratio of skilled to unskilled workers increases, the demand for low-skilled work simultaneously increases.

Regarding the second claim, consider the wage ratio between high- and low-skilled labor, $\omega = w_h/w_l$ (for convenience, we will consider the log ratio.) It is straightforward to show that this ratio depends on the state of technology and labor inputs:

$$\log\omega = \frac{\sigma - 1}{\sigma}\log\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\log\left(\frac{H}{L}\right). \tag{2.6}$$

This equation illustrates the two countervailing forces of Tinbergen's (1974) 'race' for education that govern the magnitude of the skill premium. Holding the labor supply ratio constant, and recalling our assumption that $\sigma > 1$, an increase in skill-biased technology A_H/A_L results in a larger $\log\omega$. On the other hand, holding technology constant, an increase in the proportion of workers providing high-skilled labor should decrease the log skill premium.[2] In this model, a rising skill premium occurs when the first term of (2.6) dominates the second.

To review, the SBTC model claims that unless there is technical regress, wages for all skill types will always increase, and never decrease (wages should follow a monotonic path.) Second, in the presence of an increasing

[2]Formally, $\partial\log\omega/\partial(A_H/A_L) > 0$, and $\partial\log\omega/\partial(H/L) < 0$.

proportion of workers conducting skilled work, the model is consistent with either a rising or a falling log skill premium.

2.5 Alternative Perspectives on SBTC

A crucial assumption of the SBTC model is that, like the Solow (1957) growth accounting scheme, all technological change is treated as exogenous. One alternative to the canonical model of exogenous skill-biased technological change is presented by Beaudry and Green (2005). They consider technical change as a discrete event, and model two 'modes of production' as two separate production functions: the 'old' and the 'new.' In their model, the transition to the new technology is gradual, as capital of the old type is gradually replaced by the new. Importantly, their model implies that any inequality caused by the change in technology should eventually *narrow* as more capital is invested in the new technology, and the economy switches over to the new mode of production. At the point of the new technology's invention, only a small fraction of the economy is earning higher incomes by exploiting the new technology. But as the transition to the new type of technology completes, this difference should fade completely. Applied to skill-biased technology that exhibits capital-skill complementarity, this model implies that further investments in computer technology should actually *decrease* between-group inequality.

Card and DiNardo (2002) criticize the broad acceptance of SBTC: they concede that technology is a source of changes to the wage distribution, but argue that its importance as a driver of inequality is overblown. They argue that the coincidental timing of the rise in inequality and the emergence of the personal computer gave undue salience to SBTC, overshadowing other explanations such as the decline in union membership and the transfer of manufacturing jobs to outside of the United States.

The most important critique of SBTC was, in fact, a refinement of it. Autor et al. (2003) pointed out that the notion of 'skill' was unhelpful in a model of technical change arising from computers and telecommunications technology. They argue that, although computers are a complement to certain occupations that involve a high degree of cognitive work, they tend to be a substitute for other types of routine activities, such as filing clerks and salespersons. Computers, despite their sophistication, are only capable of performing a very limited set of simple, routine tasks. They excel at processes which require calculation and simple symbolic manipulation, and are not prone to the same types of errors as human workers. It is this fact which has led to their widespread adoption in a wide range of electronic service delivery such as ATMs that were formerly the domain of human personnel. Yet, any task that requires abstract thought or physical coordination, however elementary they may appear to a human worker, is out of reach for a computer. Activities such as stacking shelves or driving a taxi are areas in which, for the moment at least, human workers enjoy a competitive advantage.

2.6 The 'Task Approach'

The approach taken by Autor et al. (2003), and the literature that followed, differs from the neoclassical approach to production in a fundamental way. The neoclassical production function, which views aggregate economic output as a simple function of inputs such as capital and labor, does not consider the specifics of the processes which produced that output (Acemoglu & Autor, 2011). Although the canonical approach has been very successful in explaining aggregate output levels, it is not sensitive to qualitative changes in the nature of production such as changes in the technology which produce output:

$$\text{capital, labor} \xrightarrow{F(\cdot)} \text{output.}$$

The *task approach* presents an alternative perspective. Rather than viewing output as a direct function of resource inputs, as in the neoclassical approach, it includes the tasks performed by labor and/or technology as an additional layer of indirection between factors and production. Under this setup, the same tasks can be performed either by capital or labor, and the two factors can even compete for the role of performing certain tasks. It then becomes the domain of the economic model to explain which factors were assigned to which tasks (Autor, 2013; Acemoglu & Autor, 2011):

$$\text{capital, labor} \xrightarrow{\text{assignment}} \text{tasks} \xrightarrow{F(\cdot)} \text{output.}$$

By separating the factors that produce tasks, and the tasks required for production, this approach facilitates the inclusion of worker *skills* in the model. For the purposes of this analysis, we follow Autor (2013) in viewing a *task* as a discrete unit of work, which may be used to create final goods and services, and a worker's *skill* as the stock of capabilities for the execution of those tasks. Importantly, under this framework, the allocation of workers' skills to tasks is considered endogenous to the model: heterogeneous workers apply their skills to tasks where they enjoy a competitive advantage.

Under this framework, the performance of tasks is not confined to human workers. Since the industrial revolution, investments in labor-saving capital by firms has seen a dramatic change in the performance of repetitive tasks. The pace of technical change has been continual: as automated looms replaced hand-weavers in the 18th century, so too are cheap computers replacing administrative clerks and service workers in the 21st century. As Brynjolfsson and McAfee (2011) point out, there is no economic reason to expect that, as jobs formerly performed by humans are replaced by computing capital, that new opportunities for workers skilled in that type of labor will arise. The phenomenon of firms substituting capital equipment for repetitive human labor was the driving force behind the industrial revolution (Goldin & L. F. Katz, 1998). There is no reason to expect that the present trend of wholesale substitution of capital for human labor will not continue.

The level and price of task-performing labor can be viewed as an outcome of the demand for particular tasks from workers and machine capital, and the supply of task-performing labor and capital. Unlike the canonical model, where technology is viewed as factor-augmenting, technology can therefore be viewed as substitutes for some tasks, and complements for others. Thus, firms are able to substitute between capital and human workers for the execution of certain tasks.

In recent decades, the most important source of labor-saving capital has been information and computer technology (ICT). As the real cost of computation has fallen precipitously over the 20th century, computers have been able to execute a wider range of tasks at a lower cost. In the presence of falling costs of ICT, the question of work force polarization can thus be framed as an outcome of a decline in the real cost of computing capital, relative to the wage cost of human workers performing similar tasks.

It is therefore plausible that the widespread adoption of ICT is a major driver of compositional changes in the workforce.

Since the late 1990s, both in Europe and the United States, the data show a marked polarization in the work force (Goos & Manning, 2007; Autor, L. F.

Katz, & Kearney, 2006). This polarization has simultaneously manifested in *wages* and in *jobs*: both wage growth and growth in the level of employment are concentrated in high-skill jobs, and to a lesser extent, the bottom end of the skill spectrum. Middle-skill jobs have stagnated since the 1990s, both in terms of remuneration and level. The recent rise of ICT investment by firms has been attributed to this trend, both because many middle-skilled jobs can be substituted by computer capital, and because communications technologies enable firms to outsource non-customer-facing roles to remote locations in order to take advantage of cheaper labor.

2.7 Capital-Labor Substitutability

To operationalize their concept of separate tasks and factor inputs, Autor et al. (2003) propose a simple model where the inputs to production are two types of tasks: 'routine' and 'nonroutine.' In this context, 'routine' has a very particular meaning: it refers to tasks that can be easily codified into computer programs or performed by machinery, such as adding up a column of numbers, or conveying a message from one place to another. This notion of routineness differs from its usual, colloquial definition. Mundane tasks such as sweeping a floor or stacking shelves, that are not (yet!) candidates for replacement by machines, are not 'routine' under this definition. Nonroutine tasks include all other tasks, including cognitive tasks, such as high-skill professional and managerial work, and low-skill manual work, where physical coordination and strength are an important part of the job.

The linkage between routine and nonroutine tasks is simple. There are three factors of production: computing capital (C), routine labor (L_R) and nonroutine labor (L_N), where all three are measured in efficiency units. Nonroutine tasks can only be performed by labor (their relationship is one-to-one), and routine tasks can be performed *either* by routine labor, or by computer capital. Autor et al. (2003) employ a Cobb-Douglas production function:

$$F(L_R, L_N, C) = (L_R + C)^{1-\beta} (L_N)^{\beta} . \tag{2.7}$$

Since routine labor and computing capital are substitutes, (2.7) implies that under competitive conditions, the price of routine labor is pinned down by the cost of computer capital. Autor et al. (2003) show that, at equilibrium, a decrease in the cost of computer capital (and hence routine labor), will cause the demand for routine task inputs to increase, as firms substitute towards the cheaper factor of production. As a result, the level of production increases. Since routine and nonroutine tasks are imperfect substitutes in production, a decrease in the cost of routine task inputs also causes an increase in the demand for non-routine tasks. So, if the supply of non-routine labor is fixed, then the relative price paid to non-routine labor increases.

To summarize, as the cost of computing capital decreases, the wage rate and demand for routine labor will decrease, and the demand for and wage paid to non-routine labor will increase. Autor et al. (2003) posit that, if individuals have heterogeneous allocations of skills, then those individuals in this economy would increasingly choose to supply non-routine labor, according to their comparative advantage. In this sense, the model can be described as 'Ricardian,' and bears similarity to Ricardian trade models, since individuals compete according to their comparative advantage.

The relatively informal model of technology-skill substitutability developed in Autor et al. (2003) offers a useful explanation of the evolution of wages for routine jobs. However, it is simple, and does not consider general equilibrium effects, nor is it capable of a more nuanced analysis of the real-world labor market. More comprehensive models of self-selection are associated with the assignment literature, and extend from Roy's model of self-selection, which we describe now.

2.8 Roy's Model of Occupational Choice

The economic insight behind many models of assignment step from Roy's (1951) model of self-selection, where individuals are endowed with heterogeneous skills, and can select between multiple occupations according to their own comparative advantage. In its most general form, the model is sophisticated enough to handle any number of occupations, and distributions of skills. For our purposes, let us here review Roy's original simple thought experiment, which takes place in a fictitious remote village situated on the banks of a river, and near a large forest. In that village, individuals with heterogeneous skills must choose between one of two occupations: hunting rabbits and fly fishing.

The level of skill required to practice these jobs is quite different: hunting rabbits, which are described as 'slow and stupid,' is easy. As a result, the return to rabbit hunting skills is not particularly great: skilled trappers will not catch many more than unskilled trappers. Fly fishing, by contrast, is extremely difficult. In this occupation, the return to skill is considerable: unskilled fishermen will hardly catch anything, but those who have mastered the art can make a good living.

In the model, the wage accrued to each activity arises from the sale of what is caught. Both fish and rabbits fetch a well-known market price, and an individual's wage is determined simply by the product of the market price and the size of the catch. It is assumed that individuals make their labor supply decisions based only on their wage; if the distribution of each type of skill is continuous, then individual agents will (almost) never be indifferent between the two activities.

Roy's intention was to explain the *selection effect*, or the difference in productivity of individuals in a given occupation relative to the population mean, as a result of their own self-selection decisions. For illustrative purposes, we present here a simple parametric example with two occupations from Heckman and Taber (2008). Although this simple example has considered only two occupations, Roy's model can be generalized to any number of occupations; the intention here is to illustrate the intuition behind the model, rather than derive a general result. Assume first that individual i's efficiency follows a bivariate normal distribution with covariance $\mathbf{\Sigma}$, where an individual would catch either F_i fish, or R_i rabbits, depending on the occupation selected:

$$\begin{bmatrix} logF_i & logR_i \end{bmatrix}' \sim N(\boldsymbol{\mu}, \mathbf{\Sigma}),$$

where $\mathbf{\Sigma}$ is a 2×2 matrix that is not necessarily diagonal. If the market prices for fish and rabbits are π_f and π_r respectively, then it can then be shown that the average productivity in each sector is

$$E\left[\ln F_i | \pi_f F_i \geq \pi_r R_i\right] = \mu_f + \frac{\sigma_{ff} - \sigma_{fr}}{\sigma} \lambda \left(\frac{\ln \pi_f - \ln \pi_r + \mu_f - \mu_r}{\sigma} \right) \quad (2.8)$$

for fishing, and

$$E\left[\ln R_i | \pi_r R_i \geq \pi_f F_i\right] = \mu_r + \frac{\sigma_{rr} - \sigma_{rf}}{\sigma} \lambda \left(\frac{\ln \pi_r - \ln \pi_f + \mu_r - \mu_f}{\sigma} \right) \quad (2.9)$$

for rabbit hunting, where σ^2 is the variance of individuals' skill ratios, $\ln(F_i/R_i)$, and $\lambda(\cdot)$ is the inverse Mills ratio.

The second terms on the right-hand sides of (2.8) and (2.9) are *selection* *effects*, and must be positive for at least one of the occupations. Specifically, the selection effect is positive for occupations with high skill variance, that is, those occupations that reward high skill levels and punish low skill levels. Whether there is positive selection into occupations with *lower* variance depends on the covariance with other skills (σ_{fr} in this example.)

Equations (2.9) and (2.8) yield rather intuitive comparative static predictions in the event of a market price change for one of the goods. In the event of a price shock (which may result from a shift in either demand or supply), agents will self-select into the market where prices have increased. For example, if the relative log price of rabbits ($\log(\pi_r) - \log(\pi_f)$) increases, *ceteris paribus*, then $\pi_r R_i \geq \pi_f F_i$ will be true for some proportion of marginal agents who had formerly been better off fishing. These marginal agents will transfer into the rabbit-hunting occupation, which has a secondary effect of reducing the observed wage dispersion in the fishing occupation.

This intuitive comparative static prediction forms the basis for the empirical analysis we undertake in this chapter. If the polarization hypothesis suggested by Autor et al. (2003) is correct, then the demand for routine and offshorable occupations should have decreased in the period 1981-2010. As wages fall, individuals transfer into other occupations, and consequently a decrease in both the level and dispersion of wages in these occupation should be observed.

2.9 ‘Ricardian’ Models of the Labor Force

By extending results from the assignment literature, a number of authors have developed more comprehensive models of worker self-selection in the presence of more than two or three types of labor or goods. Costinot and Vogel (2010) make use of a Dixit-Stiglitz production function to generalize the simple Autor et al. (2003) model to a continuum of types of workers that produce a continuum of goods in the context of international trade. In this model, and much like the simple Roy model outlined above, workers self-sort along the continuum of workers according to their own comparative advantage.

The model of Costinot *et al.* is modified by Acemoglu and Autor (2011) to explicitly separate the roles of tasks and labor. Although we do not implicitly attempt to estimate this model in the following chapters, it is worth discussing it in some detail because its implications give a good description of the 'routinization' and 'polarization' hypotheses, which we do test.

Acemoglu and Autor (2011) analyze an economy with a single output good, Y, that is produced on a continuum of tasks on the unit interval. They combine the output level y_i of each task $i \in [0, 1]$, where the output good is the numeraire, using a Cobb-Douglas production function:

$$\log Y = \int_0^1 \log y_i \; di$$

In this model, there are three types of labor: low (L), medium (M) and high (H). Each type of labor, along with capital k_i, can perform each task i, according to the production function,

$$y_i = A_L \alpha_{L,i} \ell_i + A_M \alpha_{M,i} m_i + A_H \alpha_{H,i} h_i + A_K \alpha_{K,i} k_i.$$

Productivity schedules for each task i are given by $\alpha_{L,i}$, $\alpha_{M,i}$ and $\alpha_{H,i}$. Differences in these schedules afford each worker a different comparative advantage in different tasks.

To model a spectrum of task complexity, the model assumes that complexity is increasing in the task index, with $i = 0$ being the least complex task and $i = 1$ the most complex. It is further assumed that $\alpha_{L,i}/\alpha_{M,i}$ and $\alpha_{M,i}/\alpha_{H,i}$ are continuously differentiable and monotonically decreasing, and that $\alpha_{L,i} \leq \alpha_{M,i} \leq \alpha_{H,i}$. Even though high-skilled workers enjoy an absolute advantage over medium-skilled workers, and similarly medium-skilled workers over low-skilled workers, *comparative advantage* remains, and determines the allocation of tasks among workers.

Acemoglu and Autor (2011) show that, as an outcome of self-selection, an equilibrium exists and is stable. They further show that, in equilibrium, boundaries I_H and I_L will emerge on the unit interval, such that high-skilled workers will perform tasks where $i \in (I_H, 1]$, medium-skilled workers will perform tasks where $i \in [I_L, I_H]$ and low-skilled workers will perform tasks where $i \in [0, I_L)$. Relative wages then depend on labor supply and the location of the task thresholds, which in turn depend on the comparative advantage parameters:

$$\frac{w_H}{w_M} = \left(\frac{1 - I_H}{I_H - I_L}\right)\left(\frac{M}{H}\right) \qquad \text{and} \qquad \frac{w_M}{w_L} = \left(\frac{I_H - I_L}{I_L}\right)\left(\frac{L}{M}\right).$$

The comparative statics of the model accord with what one might intuitively expect. In the event of a rise in the high-skilled technology A_H, *ceteris paribus*, the fraction of tasks performed by high-skilled labor increases (I_H decreases), and the relative wage rates w_H/w_M and w_H/w_L increase. However, w_M/w_L decreases, because H and M are closer substitutes than H and L. Correspondingly, an increase in the high-skilled labor supply H, *ceteris paribus*, increases the fraction of tasks performed by high-skilled labor, but in this case the relative wage ratios w_H/w_M and w_H/w_L *decrease*.

The model can be extended to consider labor-replacing capital, by introducing capital that competes with one or more of the types of task inputs in the model. In the case of the Autor et al. (2003) hypothesis, this capital would compete with the middle-skilled labor, M. The model predicts that, in this case, the range of tasks performed by middle-skilled labor decreases, so that the middle-skilled labor supply, M, decreases overall. However, the presence of a competing technology places pressure on the margins of middle skilled work, I_L and I_H. The relative movement of these margins depend on the relative productivity of high- and low-skilled labor at performing marginal tasks, relative to the displaced medium-skilled workers. If middle-skilled labor holds a comparative advantage over low-skilled workers, then low-skilled workers will be displaced, and the high-low wage ratio w_H/w_L will increase.

The 'polarization' hypothesis, in this model, corresponds to the presence of a labor-replacing technology in the middle of the skill distribution, and a comparative advantage for high-skilled workers relative to low-skilled workers at the margins with the middle-skilled technology. We expect to observe an increase in low- and high-skilled relative wages, but a larger increase in the high-skilled wage rate. We further expect to observe a sinking share of workers supplying middle-skilled labor, and those displaced workers moving *down* the task distribution.

A similar prediction applies for the displacement of workers by offshoring, since it is workers in the middle of the skill distribution whose jobs are replaced. In this case, though, workers are not replaced by technology, but instead by workers in foreign countries, who perform their jobs remotely via telephone or computer networks.

2.10 Summary

In this chapter, we have considered models of the relationship between technology and income of increasing detail. We saw that, in the growth literature, little allowance is made for different types of work, and as such 'technology' is assumed to operate evenly over the entire work force. These models are unable to assess the impact of skill-biased technology.

There is a wide range of models of changes in the wage profile, inspired by the rising differential between college and non-college educated workers in the United States. The most widely accepted of these, the 'canonical' model of skill-biased technical change, considers an economy with two types of labor that are imperfect complements. The model predicts that, in the face of increasing technology for high-skill workers, that wages will rise for both worker types, and that wages should be monotonically increasing over time, as well as across the skill spectrum.

Finally, we considered more nuanced models of technical change, where the discriminating factor was not 'skill', but rather the nature of the job. In doing so, we discussed the 'task approach', where occupations are considered in terms of their activities, and some activities are ripe for replacement with computers. Under the routinization hypothesis, jobs in the middle part of the skill spectrum (especially clerical and sales work) are candidates for routinization and replacement. Similarly, the same sorts of jobs should be candidates for replacement with foreign labor, by outsourcing.

In the next chapter, we will review some of the empirical evidence for changes in workers' wages, both overseas and in the Australian labor market.

Chapter 3

Empirical Literature

In this chapter, we review empirical evidence for the models discussed in Chapter 2. To some extent, the distinction between the theoretical and empirical literture is artificial: models of wage differentials and technology are difficult to separate from the empirical regularities that they describe. Nonetheless, in this section, we discuss four broad classes of studies.

First, we briefly discuss results from demographic studies of the work force. These 'model-free' studies are important because they provide the empirical regularities that models are intended to explain. Second, we look at estimates of skill changes, based on classification schemes and other measures. Third, we discuss estimates of neoclassical models of the labor force, in which model parameters are calibrated to mean values derived from survey and aggregate data. Finally, we review some examples of decomposition-type studies, in which non-parametric and semi-parametric evidence for wage-setting models are drawn from empirical wage distributions.

There is a large body of evidence for upskilling and polarization in foreign labor markets; indeed this evidence prompted much of the research into skill-biased technical change. We touch briefly on these studies, but where possible, our focus here is on Australian research. Somewhat surprisingly, while one of the key explanations for SBTC includes globalization and the worldwide proliferation of new technology, the evidence for SBTC in Australia does not align with the US and European experience. Many Australian studies have confirmed a growing demand for skilled labor, as well as an associated growth in its supply, however there is less evidence for SBTC in Australian wage data.

3.1 Direct Measures of SBTC

One way to determine whether technology is skill-biased is to directly analyze the properties and wage distributions of jobs that use new technologies. One advantage of this type of study is the absence of an explicit economic model—so the results are less susceptible to specification biases. To support the SBTC theory, two regularities should be verified in survey data: first, technology adoption should be growing, and that the nature of work changes as a result (the existence of technical change). Second, one expects to see that the impact of this technology falls primarily on the work of those with 'high' skills (the existence of skill bias).

Qualitiative research on the nature of computerization in foreign labor markets strongly supports the claim that technology changes workplaces. Evidence from the US Current Population Survey confirms that, during the 1980s and 1990s, there was indeed an increased incidence of computer use in the workplace. Between 1984 and 1997, the data show that the proportion of individuals using computers at work increased from 24% to 51% (Friedberg, 2003). Furthermore, evidence from the 1990s shows that the introduction of new technology results in a substantial rearranging of work patterns. Levy and Murnane (1996) studied the application of new technology to automate tasks in a financial services firm. He found that, although technology simplified many of the processes, those that were not automated became more complicated. Similarly, Autor, Levy, and Murnane (2002) studied the introduction of digital check imaging in a large bank, and found that, while many 'routine' tasks were easily automated, substantial changes occurred in those tasks that could not be performed by machines. Bresnahan et al. (2002) offers evidence that the introduction of computers into workplaces often incurs significant adjustment costs, including re-training, re-organization, and so on.

A limited number of surveys have been conducted in Australia. Borland, Hirschberg, and Lye (2004) analyze a cross-sectional survey of Australian workers, the 1993 ABS Training and Education Experience Survey (TEES). This survey included detail of workers' skills and depth of computer knowledge, as well as interval-censored earnings information. Using interval regression techniques, Borland regressed a number of human capital, experience and job characteristic variables against income, worker characteristics and proxies for skills, as well as a categorical variable concerning computer use and experience.

Without proxy measures of unobservable ability, the return to computer use in 1993 is estimated at 18 per cent of earnings; however, once controls are included, this effect reduces to about 8 per cent. One problem with this type of study is that, since computer use is associated with high-skilled work, unobserved ability is likely to be correlated with computer use. Despite the inclusion of measures of individual skill and ability, this means that the return to computer use cannot be exactly identified. Nonetheless, this study does strongly suggest the presence of a skill premium in the Australian labor market.

3.2 The 'College Premium'

Beginning in the 1980s, a divergence between the rental rates of skilled and unskilled labor began to emerge in the US. Acemoglu and Autor (2011) report that the 'skill premium' paid to college-educated workers remained relatively steady between 1964 and 1980, oscillating in the range of between 48 and 58 per cent above that of other workers, if other factors are held constant. However, from 1980, this premium increased steadily, far outpacing the growth rates of other types of labor, dramatically increasing wage inequality between income groups. This trend was documented using CPS microdata by Karoly (1992) and L. F. Katz and Revenga (1989), among others, using reported educational attainment to classify individuals into groups.[1] These studies also identified an intensification of the proportion of workers in the US with tertiary qualifications. To some extent, there were factors unrelated to the work force that could explain this jump in educational attainment: in the 1970s, students who continued college study were exempt from service in Vietnam, and returning veterans were granted scholarships via the G.I. bill (Acemoglu & Autor, 2011). Nonetheless, the two labor market trends emerging from this literature were a continual 'upskilling' of the workforce since the 1980s, and a steady increase in the 'college premium', the average premium paid to workers who had attained college degrees or higher.

3.2.1 Upskilling in Australia

'Skills' in the Australian labor market have been identified in empirical studies using (at least) two methods. The first, as with the US studies outlined

[1] The US experience was not universal: L. F. Katz and Revenga (1989) found, for example, that Japanese wage differentials had not followed the same pattern.

above, is to use educational attainment. The second is to use occupational group as a proxy for skill.

In sample surveys, occupations must be coded according to some consistent scheme in order to be comparable across the sample surveyed, and also across time periods. The occupational classification schemes used in Australia, such as the ASCO (Castles, 1986), and the ANZSCO (Trewin & Pink, 2006), typically include a 'skill level' ranking for each coded occupation. The ASCO II, defines skill level as 'a function of the range and complexity of the set of tasks involved' (Castles, 1986, p.14), and is a combination of the level of education and experience required for classified occupations. The use of these skill metrics have been criticized, but they do provide useful categories for analysis of the skill distribution.[2]

Cully (1999) divides employment data into five broad skill groups, and analyzes changes in the number of jobs in each category between 1986 and 1997.[3] He finds that, over this period, there was growth in the high- and low-skilled jobs, but that the number of jobs in the middle categories was stagnant or declined, lending some support to the polarization hypothesis. However, in line with international evidence, the dominant pattern in the data is growth in high-skilled jobs, or 'up-skilling.' A similar conclusion is reached by Wooden (2000), who expands Cully's methodology to also consider growth in terms of hours worked.

A more recent analysis of the skill distribution was undertaken by Esposto (2012), adopting the aggregation approach taken by Cully (1999),

[2] Cully (1999) argues their use originates from the need to place employees in a social class, rather than analyze the skill intensity of the work. However, it is not clear that these skill levels are any worse than the use of educational attainment as a skill proxy.

[3] These groups are aggregations of the top-level groupings given in the ASCO, and are the same was those later used by Wooden (2000) and Esposto (2012). The skill groupings are, (1) managers/professionals, (2) associate professionals, (3) skilled vocations, (4) intermediate skills, (5) elementary skills.

but using a longer sample and Census data, between 1971 and 2006. By recombining the 1971 census data, which was coded using an obsolete coding scheme, to suit the ASCO II classification, Esposto was able to create a comparable series of the levels of occupations over this 35-year period. Novel in Esposto's analysis is a breakdown of full-time and part-time work, a distinction that has grown in importance over the 2000s.

Esposto found that, between 1971 and 2006, the skill intensity of the Australian labor market increased, as measured by a greater proportion of the work force employed in high-skilled occupations. The greatest growth was observed in the top category, professionals and managers (115.5 per cent), and the two lowest skill categories, intermediate and elementary skills, also grew (54.5 and 22.5 per cent, respectively). The middle category, 'skilled vocations' shrank by 7.4%, suggesting job polarization. Furthermore, Esposto disaggregated part-time and full-time jobs, and found that full-time jobs predominantly experienced upskilling, whereas part-time and casual jobs experienced down-skilling, especially for males.

3.2.2 A 'Uni Premium' in Australia?

Somewhat surprisingly, a college premium is not readily apparent in the Australian data. Barnes and Kennard (2002) analyze household survey data, and use educational attainment as a proxy for skill. They find that, over the 1980s and 1990s, growth in the demand for high-skilled far outpaced that of low-skilled workers. In the 1980s, the demand for skilled employment grew at a rate of 4.7 per cent per year (against 0.5 per cent annually for unskilled unemployment), and in the 1990s, the growth rates were 3 per cent and 0.8 per cent, respectively.

In contrast to the American and European experience, Barnes and Kennard (2002) find no evidence of a skill premium. Using industry measures as proxies for demand, the authors attempt to decompose the differences between relative demand and supply for each type of labor, and find negligible discrepancies. They conclude that the lack of a college premium is due to the supply of both types of labor expanding at the same rate as their respective demands, creating no scarcity premium in the labor market.

No college premium was found by Coelli and Wilkins (2009), who followed a similar procedure to Katz and Murphy (1992). the authors employ both income survey microdata and census samples to estimate the premium paid to university graduates, in excess of those without university degrees, between 1981 and 2004. Like Barnes and Kennard (2002), Coelli and Wilkins find that, that although a university premium exists, it is not rising, as it is in the United States and Europe.

Coelli suggests a novel explanation for the absence of a rising wage premium for degree-qualified labor. First, they note differences between the Australian and US system of tertiary qualifications. In the US, bachelor degrees take four years to attain, but in Australia, three-year degrees are the norm, suggesting that the attaiment of a three-year degree. They also point out that changes to higher education funding arrangements in the 1990s have broadened the scope of teritary degrees tremendously, so that many degrees now cover skills that would previously have been taught at technical colleges such as TAFE. If the scope of what is taught at universities is expanded to include skills not normally associated with high-skilled work, then a relatively smaller proportion of university graduates will be observed to be in high-skill, high-earning occupations, and the measured college premium will be lower.

3.3 Models of SBTC

Recall from Chapter 2 (§2.4) that, as the technology coefficient associated with high-skilled workers increases, the canonical model of SBTC predicts a rising premium to be paid to high-skill workers. Indeed, evidence from the United States and Europe support this claim.

Katz and Murphy (1992) estimate a version of the college premium, as described in (2.6). To do so, they assume an exponential functional form for the evolution of the technology ratio, A_H/A_L, over time,

$$(A_H/A_L)(t) = A_0 e^{A_1 t},$$

where A_0 and A_1 are constants. When substituted into (2.6), this yields a regression model of the following form:

$$\log \omega_t = \frac{\sigma - 1}{\sigma}\beta_0 + \frac{\sigma - 1}{\sigma}\beta_1 t - \beta_2 \log\left(\frac{H_t}{L_t}\right) + \epsilon_t, \tag{3.1}$$

where $\log(H/L)$ is the log wage share ratio. Using data from 1963 to 1987, they estimate

$$\log \omega_t = \kappa + \underset{(0.007)}{0.033}t - \underset{(0.150)}{0.709}\left(\frac{H_t}{L_t}\right),$$

where κ is a constant. This model implies a college premium rising at a rate of approximately 3.3 per cent annually.

As Acemoglu and Autor (2011) point out, this model predicts the rise in the college premium over the 1990s reasonably well, although it does under-predict the true level of between-group inequality somewhat from 2002 onwards.

3.3.1 SBTC in Australia

Under the canonical model, the proportion of high-skilled labor employed should increase in the presence of SBTC. Using industry-level data between 1978 and 2000, de Laine, Laplagne, and Stone (2001) analyze the changes in shares of skilled and unskilled labor, identified by educational attainment. They find that both the total wage bill and share of employment of skilled workers has increased dramatically, across all industries, in Australia over this period.

They further test whether technology investment or technology use indexes can explain this evolution. To do so, they employ a variety of functional forms, including a CES production function and a flexible (translog) model to estimate changes in the shares of high-skilled labor, as a function of R&D spending, capital growth and a technology index.

The manufacturing industry, when entered alone, shows a strong relationship between the share of skilled workers and technological change. However, the authors find that this relationship is weaker for other industries. De Laine et al. (2001) find that the relationship strengthens in the 1980s, and posit that this period of extensive microeconomic reform allowed firms greater flexibility to adopt new technologies requiring a more highly skilled work force.

3.4 Occupational Task Measures

As DiNardo and Pischke (1997) point out, the assumption that changes in wage premia observed the last two decades of the 20th century are due to technological change may incorrect, or overwrought. Indeed, there are several competing models capable of explaining this trend (§2.2). In the literature of the 1990s, the argument for SBTC rested upon two pieces of evidence: timing (the changes occurred at a time when the proliferation of personal computers and networking was highest), and the simple observation that high-skilled work is best suited to take advantage of the new technology. One way of testing the association between technology and wage changes is direct ethnographic research, conducted at the firm level, discussed above (§3.1).

Unless the data can be augmented to include some measure of the properties of occupations coded in survey data, econometric analysis cannot draw conclusions about the types of jobs that are most affected by technological change. We have seen above (§3.2.1) that 'skill' data in occupational classifications can inform analysis to some degree, but this information does not discriminate between the types of skills that are impacted by changing technology. Fortunately, the occupational classification schemes provided by the US Department of Labor, published as *The Dictionary of Occupational Titles* (DOT) between 1939 and the 1990s, and *O*NET*, an electronic database, first released in 1998, *do* include detailed 'task' information, along with occupational titles. The 2010 edition of the O*NET includes a taxonomy of 921 occupations, as well as detailed information about each of these occupations on a large number of quantitative scales. A more detailed discussion of the O*NET data can be found in the appendix (§B.2).

The use of the DOT and O*NET database as the basis for analytical studies of the work force is not new, nor is it exclusive to the Economics literature. Sociologists Cain and Treiman (1981) review a considerable sociological literature that employs the DOT's quantitative scales to analyze changes in the wage distribution. They show that, although there is considerable redundancy in the DOT's 44 measures, and although certain job characteristics (such as authority relationships and seniority) are missing, they contain at least as much information as many scales built specifically for the purposes of sociological analysis.

The detailed job criteria available in the DOT and O*NET have been exploited to explore the relationship between jobs' characteristics, and changes in the both the share of employment and the wage profile. Autor et al. (2003) use the DOT to construct indexes for 'routine' and 'cognitive' components of jobs, that they regress on employment levels and wages across industries in the United States. They show that this model explains a considerable proportion of the dispersion of wages in the United States between 1960 and 1998, and that computerization led to a substitution in the observed levels of employment, away from routine tasks and toward cognitive tasks.

The O*NET data have been exploited in foreign jurisdictions as well. By mapping UK job codes to O*NET codes, Goos and Manning (2007) find a similar trend in the United Kingdom: between 1975 and 2003, there was an increase in the number of high-skilled, high-wage (which they dub 'lovely') jobs, as well as low-wage, low-skilled ('lousy') jobs, but a relative decrease in the number of 'middling' jobs. In a subsequent paper, a similar pattern was found for Continental Europe (Goos, Manning, & Salomons, 2009).

For Australian data, Esposto and Abbott (2011) performed a mapping between the O*NET classfication and the ASCO II. Using the O*NET data, they construct a 'knowledge intensity' index, which they take to be a proxy for 'skill.' They find that the Australian work force, overall, has increased in its knowledge intensity between 1971 and 2006. However, they also find that the distribution of knowledge is shifting: away for men and toward women, and away from part-time workers and toward full-timers.

3.5 Wage Profile Decompositions

The evidence considered above suggests that, over time, the skill distribution of both the US and Australian populations has been shifting. A greater proportion of both populations has attained tertiary degrees, for example, and women's work force participation patterns have changed. This presents a problem for comparing wage profiles over time. A direct analysis of the wage profile, without knowledge of changing composition of the work force, cannot determine whether any observed changes occurred as a result of changing human capital variables, such as experience and educational attainment, or as a result of structural factors, such as technological change (see, e.g. J. A. Mincer, 1974).

3.5.1 A Reweighting Approach

Reweighting techniques overcome the problem of composition effects by computing a 'counterfactual' distribution, that has the same distribution of covariates as the comparison distribution. First, suppose we have a set of observations, in which individuals can either be observed in period 0 or 1.

The goal of this approach is to re-weight the observations in period 0 so that the covariates in period 0 match those in period 1. Adopting the re-weighting procedure suggested by DiNardo, Fortin, and Lemieux (1996), they aim to create a counterfactual wage distribution $F^C_{Y_0}$ that exhibits the characteristics of period 0, but with the wage structure of period 1:

$$F^C_{Y_0} = \int F_{Y_0|X_0}(y|X)dF_{X_1}(X)$$

We now re-write this equation as an integral over $F_{X_0}(X)$, by adding a reweighting factor $\Psi(X) = dF_{X_1}(X)/dF_{X_0}(X)$:

$$F^C_{Y_0} = \int F_{Y_0|X_0}(y|X)\Psi(X)dF_{X_0}(X)$$

DiNardo, Fortin, and Lemieux (1996) show that this re-weighting factor, which is the ratio of two marginal distribution functions, can be manipulated with an application of Bayes' rule to yield a ratio of two binary outcome models:

$$\Psi(X) = \frac{\Pr(T = 1|X)/\Pr(T = 1)}{\Pr(T = 0|X)/\Pr(T = 0)},$$

that re-weights the data in period 0 to match the distribution of covariates observed in period 1. To implement this re-weighting function, the probability of T being 1 or 0 can be modeled using a probit model, fit to the combined data sets, with T as the response variable.

The DiNardo, Fortin, and Lemieux (1996) approach to decomposition by re-weighting as been used in the Australian context by Barón and Cobb-Clark (2010), who decompose the gender wage gap measured in the HILDA database into a difference explained by wage-related characteristics, and a component that is unexplained.

3.5.2 The Oaxaca-Blinder Decomposition

The Oaxaca-Blinder decomposition allows changes in the wage distribution to be attributed to a set of covariates that impact upon wages. The decomposition methods described here were first described in separate papers by Oaxaca (1973) and Blinder (1973).

Consider some outcome variable, such as an average log wage, that differs for two disjoint groups. Oaxaca, for instance, considered the difference in mean wages paid to men and women. Let the difference in the mean wage for men and women be Δ:

$$\Delta_O = E[\ln y_m] - E[\ln y_f]. \tag{3.2}$$

If Δ is nonzero, this might be explainable by (a) factors arising from different human capital endowments in each group, (b) factors arising purely from group membership, or (c) both. The goal of the Oaxaca-Blinder (OB) decomposition is to divide this difference into two components: the component explainable by human capital factors (the endowment effect), and a structural component attributable only to group membership.

To determine the influence of sex on the mean of the wage distribution, Oaxaca considered two separate regression models, one for each sex. Each vector X_i of covariates included demographic and human capital variables such as years of education, work experience and age:

$$\ln y_{g,i} = \mathbf{X}'_{g,i}\boldsymbol{\beta}_g + \epsilon_{g,i} \quad \text{where } g = M, F.$$

Then, taking expectations of both sides and substituting into (3.2), the difference of expected log wages can be decomposed as,

$$\begin{aligned}\Delta_O &= E[X_m]'\boldsymbol{\beta}_m - E[X_f]'\boldsymbol{\beta}_f \\ &= \underbrace{E[X_m]'(\boldsymbol{\beta}_m - \boldsymbol{\beta}_f)}_{\Delta_S} + \underbrace{(E[X_m]' - E[X_f]')\boldsymbol{\beta}_f}_{\Delta_X}.\end{aligned} \tag{3.3}$$

The second term of this decomposition, Δ_X, is the difference in mean log wages that can be explained by human capital factors (the 'endowments effect'). The other term, Δ_S, represents the 'structural' difference in wages between the two groups. In the case where the wages of males and females are being considered, this term can be interpreted as the sex discrimination differential. The parameters in (3.3) are computed at their means to determine the difference $E[X_m]'(\boldsymbol{\beta}_m - \boldsymbol{\beta}_f)$ attributable to discrimination, in the mean log wage.

In the SBTC literature, the object of interest is the distribution of wages, rather than differences in the conditional mean, and the two groups of interest are not gender groups, but rather two different time periods, at the start and end of the period during which technical change is suspected to have occurred. For simplicity, we refer to these time periods as $T = 0$ and $T = 1$, respectively.

3.5.3 Unconditional Quantile Regression

One major shortcoming of the Oaxaca-Blinder decomposition is that only the conditional means of a wage distribution, $E(Y|X)$, and its counterfactual can be compared. Recall that, in the Roy model described above, changes in the profitability of any occupation should result in the more efficient individuals self-selecting out of an occupation. The mean of a wage distribution is a poor instrument for observing this phenomenon: rather, any polarisation effect will be observed in the overall *distribution* of wages, F_Y. Furthermore, it may be that certain effects only occur in some parts of the wage distribution, so that measuring the distribution mean is not appropriate. Ideally, we would like to compute a decomposition similar to (3.3), but which decomposes changes in the τth quantile of the wage distribution, $q_\tau(F_Y)$. Such a decomposition was considered by Firpo, Fortin, and Lemieux (2011); it is their technique, as described in Firpo et al. (2009), that we apply here.

Under our decomposition, the wage of an individual i is observed in one of two periods, $T = 0$ or $T = 1$. Under the hypothesis of wage polarisation, we will assume that individuals are paid under two distinct wage structures: the pre-polarisation wage structure that has distribution F_{Y_0} (when $T = 0$) and the post-polarisation wage structure, F_{Y_1} (when $T = 1$). We wish to decompose the observed overall change Δ^τ in the quantile statistic, attributable to changes in work force composition Δ^τ_X and changes in the wage structure, Δ^τ_S:

$$\begin{aligned}\Delta^\tau_O &= q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=0}) \\ &= \underbrace{q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=1})}_{\Delta^\tau_S} + \underbrace{q_\tau(F_{Y_0|T=1}) - q_\tau(F_{Y_0|T=0})}_{\Delta^\tau_X}\end{aligned} \tag{3.4}$$

Notice that this decomposition depends on the availability of a hypothetical counterfactual distribution, $F_{Y_0|T=1}$, wherein the workers of period 1 are paid according to the wage structure of period 0. Although such a distribution cannot be directly observed, Firpo et al. (2011) show that a consistent estimator of $F_{Y_0|T=1}$ can be found by re-weighting F_{Y_0} to have the same distribution as F_{Y_1}.

Firpo et al. (2009) demonstrate that the aggregate decomposition (3.4), can be performed using an OLS regression on the recentered influence function of the distributional statistic in question.[4] The recentered influence function is the usual influence function used in the analysis of robust estimators, 'recentered' by adding back the value of the distributional statistic. In the case of the quantile function q_τ, the RIF is given by,

$$RIF(y; q_\tau) = q_\tau + IF(y; q_\tau) = q_\tau + \frac{q_\tau - \mathbf{1}\{y \leq q_\tau\}}{f_Y(q_\tau)}.$$

[4]Note that RIF regressions must be used in the Oaxaca-Blinder decomposition, and not quantile regressions, because the law of iterated expectations only holds for the conditional mean of a distribution, and not other functionals of the distribution. See Firpo et al. (2009) for a detailed discussion.

Then the estimated coefficient $\gamma_t^{q_\tau}$ of an OLS regression of $RIF(y; q_\tau)$ on the set of wage-related characteristics, X, is

$$\gamma_t^{q_\tau} = (E[X \cdot X'|T = t])^{-1} \cdot E[RIF(y_t; q_\tau) \cdot X|T = t]$$

Firpo et al. (2009) show that the distributional statistics themselves can be written as expectations of the conditional RIF, since the expected value of the influence function is zero, and thus $E[RIF(y_t; q_\tau)] = q_\tau$:

$$q_\tau(F_t) = E_X[E[RIF(y_t; q_\tau)|X = x]] = E[X|T = t] \cdot \gamma_t^{q_\tau},$$

And thus we can write (3.4) in a similar form as (3.3):

$$\Delta_O^\tau = \underbrace{E[X|T = 1] \cdot (\gamma_1^{q_\tau} - \gamma_0^{q_\tau})}_{\Delta_S^\tau} + \underbrace{(E[X|T = 1] - E[X|T = 0]) \cdot \gamma_0^{q_\tau}}_{\Delta_X^\tau}.$$

Under the 'ignorability' assumption, discussed in the following chapter (§4.5.1), both of these components of the decomposition are identified.

3.5.4 Hybrid Approaches

Firpo et al. (2011, p.19) point out that the RIF-regression described above is a local approximation that may not hold for large variations in covariates X. In particular, if the relationship between Y and X is nonlinear, then shifts in the distribution of X may result in different estimates for $\gamma_t^{q_\tau}$ even if Y is invariant.

Unfortunately, for labor force data stretching over a decade or even an entire generation, changes in covariates between period $T = 0$ and $T = 1$ cannot be assumed to be small. ABS data show that there are considerable differences in the composition of the labor force between 1981-2 and 2009-

10 (ABS, 2013b). The average unemployment rate in 1981-2 similar to that of 2009-10 (6.1 per cent versus 5.7 per cent, respectively), but the period was marked by considerable demographic changes. Since the 1980s, women have entered the work force in far greater numbers, and overall labor force participation patterns have varied. Between 1981-2 and 2009-10, the average participation rate for men fell from 77.7 per cent to 72.3 per cent. For women, on the other hand, the participation rate rose from 44.8 per cent to 58.6 per cent. And, for both sexes, the rate of part-time employment has increased dramatically. Clearly, the covariate distributions at both time periods are not directly comparable.

Using re-weighted data, we can estimate the means of the counterfactual distribution, $\hat{\bar{X}} = \sum_{i|T=0} \hat{\Psi}(X_i) \cdot X_i$, and the coefficients $\hat{\gamma}_{01}^{q_\tau}$ by regressing $RIF(Y_0; q_\tau)$ with the new sample weights. We then rewrite the decomposition (3.4) as the sum of two separate Oaxaca-Blinder decompositions. The first term, the wage structure effect, is decomposed into a composition effect $\hat{\Delta}_{S,p}^{q_\tau}$ and specification error, $\hat{\Delta}_{S,e}^{q_\tau}$. The second gives a similar decomposition for the composition effect:

$$\begin{aligned}
\hat{\Delta}^{q_\tau} &= (\hat{\Delta}_{S,p}^{q_\tau} + \hat{\Delta}_{S,e}^{q_\tau}) + (\hat{\Delta}_{X,p}^{q_\tau} + \hat{\Delta}_{X,e}^{q_\tau}) \\
&= \underbrace{\left([\bar{X}_{01} - \bar{X}_0]\hat{\gamma}_{01}^{q_\tau} + \bar{X}_{01}[\hat{\gamma}_{01}^{q_\tau} - \hat{\gamma}_{0}^{q_\tau}]\right)}_{\hat{\Delta}_S^{q_\tau}} + \underbrace{\left(\bar{X}_1[\hat{\gamma}_1^{q_\tau} - \hat{\gamma}_{01}^{q_\tau}] + [\bar{X}_1 - \bar{X}_{01}]\hat{\gamma}_{01}^{q_\tau}\right)}_{\hat{\Delta}_X^{q_\tau}}.
\end{aligned}$$

This decomposition can be performed on income surveys of repeated cross-sections of the same markets over time. Firpo et al. (2011) apply this technique to several pairs of cross sections between 1976 and 2010. By including occupational task measures in their set of explanatory variables, they are able to decompose changes in the unexplained portion of the wage distribution changes according to whether a job is susceptible to technological change, and the degree to which that job can be offshored. They find that technology was skill-biased during the 1980s, affected by off-shoring in the 1990s, but that from the 2000s technology effects were no longer observed.

3.6 Other Approaches

Using cointegration techniques, Gaston and Rajaguru (2009) incorporate Leigh (2005)'s income tax data in a time series model of the relationship between the Gini coefficient and macroeconomic variables, including the terms of trade, investment in ICT infrastructure, the unionisation rate, and indexes of social and economic globalisation. By applying restrictions to the resulting time series model, they are able to test Granger (non-)causality between indexes of technological change and measurements of inequality. Along with other globalization indexes, they find that technology investment, interpreted as a proxy for SBTC, Granger causes increases in the Gini coefficient. They conclude, therefore, that firm investment in new technology is contributing to a general increase in income inequality.

3.7 Summary

In this chapter, we reviewed the main empirical treatments of technological change, with an emphasis on Australian studies. The consensus in the literature is that, like other developed nations, Australia is experiencing technological change, and that this change has manifested in work force upskilling, particularly in the 1980s and 1990s.

There is little evidence to date that technological change is causing widening of the skill spectrum, a theory that has found wide acceptance for other industrialized countries. Rather, studies generally agree that as firms have shifted towards skilled labor, the supply of skilled workers has evenly kept pace with demand.

Chapter 4

Empirical Work

We now employ empirical tests to bring some of the theories outlined in previous chapters to the Australian data. We first describe our data, derived from the Survey of Income and Housing, a periodic sample survey conducted by the ABS between 1981 and 2012, and the O*NET database of occupational tasks.

The first theory we test is the standard 'canonical' model of SBTC. Second, we test a slightly more nuanced version of this model, which makes provisions for three types of labor. Finally, we test whether a Roy-type model of changes in the occupational wage structure can be explained by the task content of occupations.

We require data on real wages, as well as detailed measures of the tasks performed by participants of each occupation. For this analysis, we obtained microdata for the Survey of Income and Housing (SIH) for 1981/82, 2000/01 and 2011/12, as well as measures contained in the O*NET database, published by the US Department of Labor. Details of both the task measures and SIH are discussed in detail in the data appendix (§A.1, §B.2). We shall therefore only briefly review the salient features of the data sources as they relate to this analysis.[1]

4.1 Testing the Canonical Model

As we have seen, the 'canonical model' of SBTC explains the increase in observed inequality as a rise in the premium that accrues to high-skilled workers (§2.4). To review, the argument for an increasing skill premium, observed in the US and UK, is that advances in technology have led to an excess of demand over supply for college-educated workers (Katz & Murphy, 1992).

4.1.1 Data

The Survey of Income and Housing is a hierarchical clustered household survey conducted by the ABS every 2-3 years since 1995, and also for the fiscal years 1985/86 and 1981/82. The survey provides detailed information about respondents' labor and non-labor income sources, as well as data on age, educational attainment, hours worked, industry and occupation. For the surveys conducted between 2000 and 2010, as well as the 1981-2 survey, the data include detailed occupational codes, which will become important later. The other surveys include occupation only at the one-digit level. We obtain survey micro-data as confidentialized unit record files (CURFs).

We treat the multiple surveys as repeated cross-sectional measures of the working population. In this study, we are interested in the changing value of 'skills', not in individuals' wealth *per se*: some care needs to be taken to ensure that comparisions are consistent. Following Acemoglu and Autor (2011) and others, we consider only full-time workers, and 'composi-

[1]There are a variety of data sources available. For a discussion of our choice of the SIH, please see the appendix.

tion adjust' the workforce according to age, sex and educational attainment to ensure that any differences in incomes are not due to mechanical, demographic changes in the composition of the work force. We include only those individuals whose incomes are received as employee wages, or as the proceeds from unincorporated entities, including the value of entitlements, tips and bonuses. Revenue from government payments, investment dividends, and so on, are ignored. Nominal incomes are deflated using the CPI, averaged over the four quarters of the survey's fiscal year.

4.1.2 Results

If SBTC explained the widening of the income distribution, then we would expect to observe the premium accruing to 'skilled' labor increasing with time. In the United States, such an increase was indeed observed. There, the wage premium earned by tertiary-educated labor fell in the 1970s, but has risen each decade since then (Acemoglu & Autor, 2011). Katz and Murphy (1992) employ a similar empirical model which explains the rise of the skill premium in the United States in the post-war era. In Australia, however, a corresponding growth in the premium for tertiary qualifications has not been observed. Figure 4.1 shows the log skill premium for Australia and the United States between 1981/82 and 2008.

However, the absence of a rising wage premium does not provide sufficient evidence to invalidate the model. Recall that the growth of the wage premium is explained not simply as a function of the high/low technology ratio, but also of the relative supply and demand ratios of low- and high-skilled workers. Recall that, in the Katz and Murphy (1992) implementation of the model given by (3.1), the log wage premuium is a function of both the technology ratio (A_H/A_L) and the ratio of labor employed (H/L). Other

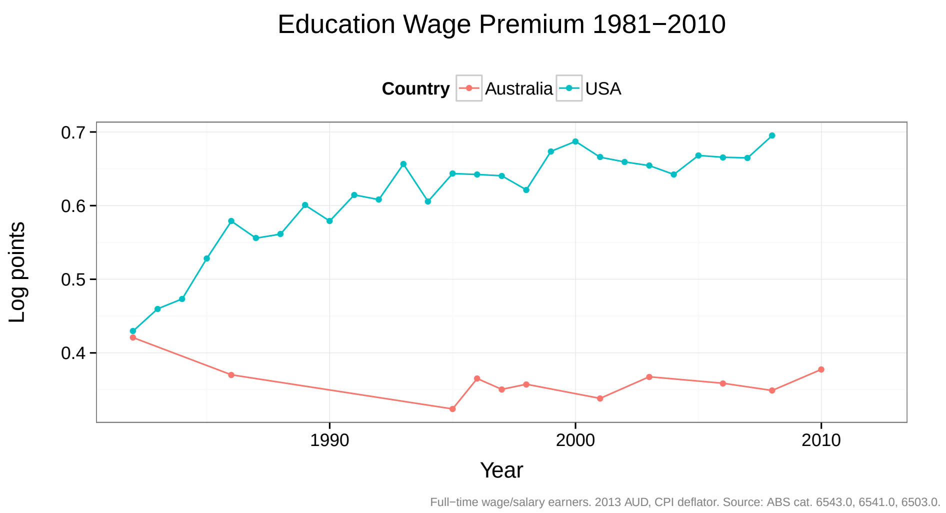

Figure 4.1: University/non-university log wage premium, Australia and the United States. The figure shows the difference between the mean log weekly income for workers who have attained a bachelor degree or higher, and the mean log weekly income of other workers. Only full-time workers whose main sources of income are wages and salaries are included, and survey data have been composition adjusted for sex, age group, (and for the United States, race). Source: for Australia, ABS Survey of Income and Housing, and for the United States, Acemoglu and Autor (2011).

authors have concluded that a similar technology trend is present in the Australian data, but that the expanding supply of skilled workers has grown in lock-step with demand, leading to no increase in the skill premium.

The canonical model implies that real wages will never decrease for either skilled or unskilled workers (Acemoglu & Autor, 2011). This gives rise to two falsifiable predictions: first, that wage growth should be increasing with skills, because higher-skilled individuals should experience greater wage growth than lower-skilled individuals. Second, wage growth should be monotonic over time. Since technology is assumed to be continually increasing, and is also assumed to be purely skill-augmenting, there is no provision in the theory for a decrease in absolute wages.

Figure 4.2 plots the cumulative change over time for three wage per-

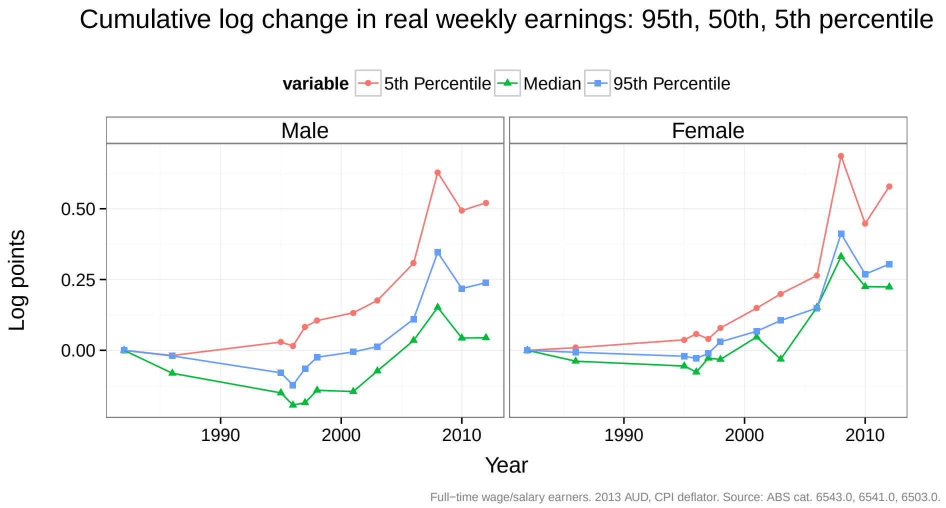

Figure 4.2: Cumulative log change in real weekly earnings, 5th, 50th and 95th percentiles, 1982-2010. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotonic for males in lower percentiles. Source: Survey of Income and Housing.

centiles, the 5th, 95th, and the median. Over the period 1981-82 to 2009-10, although wages at the top percentiles increased steadily, the same is not true for the lower percentiles. Indeed, for all of the 1990s and much of the 2000s, cumulative real income growth from 1981-82 was negative for many workers. At best, this suggests that technological change does not explain all of the observed changes in the wage distribution.

With the data we have available, we are unable to directly observe skill or individuals from period to period. We are thus unable to test the assertion that wages should be rising in the level of skill. However, Goos and Manning (2007) and Acemoglu and Autor (2011), who also only have repeated cross-sectional data available, overcome this problem by treating wage percentile as a proxy for skill levels. Figure 4.3 shows the composition-adjusted changes in log real wage by percentile, for males and females, between 1981-82 and 2009-10. If the 1981-82 income percentile can be considered a proxy for

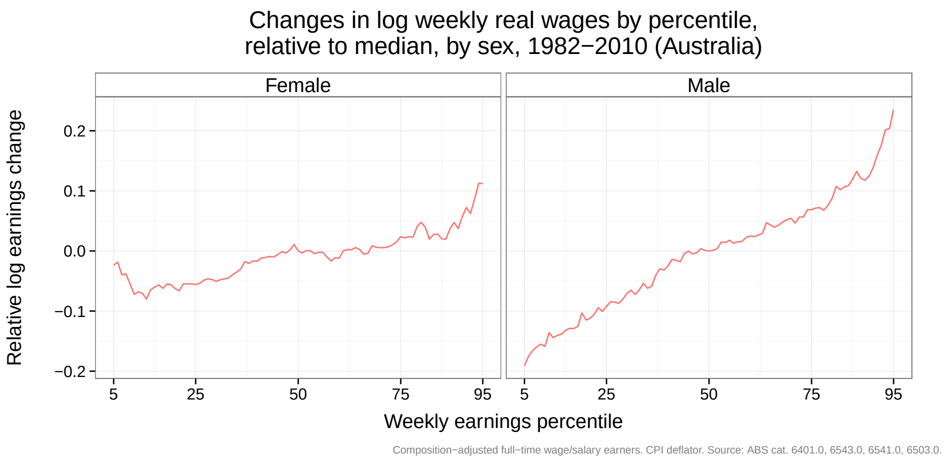

Figure 4.3: Change in weekly wage by percentile, 1981/82–2009/10, Males and Females. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotone for females in lower percentiles. Source: Survey of Income and Housing.

skill, then it is apparent that, over this period, wages grew for high-skilled individuals much faster than for low-skilled individuals. For males, wage growth is monotonic, as predicted by the model: those further up the income distribution (i.e. presumed to have higher skill levels), experienced greater wage growth. However, note that, for females, percentile wage growth is non-monotonic; the lower income quantiles experienced greater wage growth than the median.

4.1.3 Discussion

The evidence discussed in this section is only partially in agreement with the canonical model of SBTC laid out in Chapter 2. The model predicts an increase in inequality, as agents invest in education and increase the gap between 'skilled' and 'unskilled' workers. This trend is indeed observed (Figure 1.1). However, in the model, the channel through which income inequality increases is the college premium. This is not the case in Australia

(Figure 4.1). Further regularities in the data speak against the model: non-monotonicity in wage quantiles and wages over time suggest that the SBTC story may not be the most helpful explanation.

That the income distribution is widening, but the skill premium is *not* driving the change, suggests at least two interpretations. We have already discussed the fact that educational attainment may be a poor indicator of skill for the Australian labor market. A second, more nuanced explanation was suggested by Autor et al. (2003). Technological change may not be complementary to all types of labor; it may in fact be a *substitute* for certain jobs.

4.2 The 'Disappearing Middle'

The previous section suggests that, in Australia, the relationship between technology and wages are not as simple as the canonical model suggests. Evidence in the empirical literature suggests that it is middle-skilled jobs, rather than simply low-skilled jobs, that are fading from the work force over time (e.g. Harding, 1997; Cully, 1999; Esposto, 2012). We do not attempt to replicate the existing empirical literature here; evidence for slow growth in middle-skill jobs up to 2006 were demonstrated by Esposto (2012). However, for the purposes of this investigation, we will refine the SBTC model employed above (§4.1) to include a more nuanced understanding of 'skill,' following the division suggested by Autor et al. (2003).

4.2.1 Model

To test this pattern for Australian data, we can augment (2.3) by introducing a third type of labor, M, to represent work which requires mid-level skill and low levels of physical activity, representing 'routine' or 'middling' work. We also introduce computer capital, C, as a substitute in production for medium-skilled labor, and a complement in production for high-skilled workers.

First, as with the canonical model, suppose a competitive economy is governed by an CES aggregate production function which employs three types of workers: low-skilled, medium-skilled, and high-skilled. We do not necessarily require that workers of each type are homogeneous or earn the same wage. We do, however, assume that the wage, per efficiency unit, for each type of labor is fixed. As before, we call the sets of high-, medium- and low-skilled workers $\mathcal{H}$, $\mathcal{M}$, and $\mathcal{L}$, respectively. Then we can define the aggregate inputs of each worker type by summing over the inputs of each worker i, measured in efficiency units: $H = \int_{i\in\mathcal{H}} h_i \, di$, $M = \int_{i\in\mathcal{M}} m_i \, di$, and $L = \int_{i\in\mathcal{L}} \ell_i \, di$.

Crucially, the aggregate production function also depends on ICT capital, C, which is a complement in production for high-skilled workers, and a substitute for medium-skilled workers. Then, the production function is given by,

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_M M + C)^{\frac{\sigma-1}{\sigma}} + ((A_H H)^{\mu} + C^{\mu})^{\frac{\sigma-1}{\mu\sigma}}\right]^{\frac{1}{\sigma-1}}. \tag{4.1}$$

Michaels, Natraj, and Reenen (2013) use a formulation similar to (4.1) to show that, if ICT investment C increases exogenously, the wage share for high-skill workers should increase, but decrease for low-skill workers. Likewise, the wage premium for high-skilled workers should rise with increasing ICT investment, and fall for medium-skilled workers.[2] To test these pre-

[2]Following Michaels et al. (2013), we focus on the wage *share*, and not the absolute wage. Although wages for high-skilled and low-skilled workers should increase with increased investment, the comparative static predictions for medium-skilled workers are indeterminate. Michaels et al. prove that the comparative static predictions for the wage share, however, are unambiguous.

dictions, Michaels et al. (2013) specify a simple linear functional form to test the impact of ICT investment on the wage share for type of labor $S \in \{H, M, L\}$, estimated for broad industry groups across eleven countries, using educational attainment as a proxy for skill. The authors find support for the claim that ICT investment is associated with a decrease in the demand for middle-skilled labor.

Adapting their specification for Australia gives the empirical model shown below. In this model, $SHARE^S$, computed as $\sum_k W_k^S / \sum_{s,j} W_j^s$, is the wage bill share for the labor category S, C is ICT capital, K is non-ICT capital, and Q_i is value added by industry i.

$$\Delta SHARE^S = \alpha_{CS} \log(C/Q)_{it} + \alpha_{KS} \log(K/Q)_{it} + \alpha_{QS} \log(Q)_{it} + \epsilon_{it}. \quad (4.2)$$

As Michaels *et al.* point out, the polarization hypothesis is consistent with coefficient estimates where $(\alpha_{CM} < 0)$ and $(\alpha_{CH} > 0)$.

4.2.2 Data

With the results from the previous section in mind, to adapt this specification for Australia requires an alternative yard-stick for 'skill.' Following Autor et al. (2003), we perform a simple, subjective partitioning of occupations according to the tasks they involve, as described by the ANZSCO major groups. For the purposes of this very simple and informal model, we divide occupations into three categories: 'non-routine manual' (low-skilled, L), 'routine' (middle-skilled, M), and 'non-routine cognitive' (high-skilled, H). To deal with differences in occupational coding, we use the ANZSCO–ASCO II link table provided by the ABS (Table A.3).

Capital series were derived from national accounting data. Our data include measures of ICT capital, collected by the ABS as part of the National Accounts. For this study, we consider the aggregate ICT capital series, as well as two components: *software*, and *electrical and electronic equipment*. *Software* includes both commercial off-the-shelf packages, as well as custom-built line-of-business programs, whereas the second variable includes telecommunications equipment and other electronic machinery. To smooth out variation in the data, the period 1996-2010 was divided into two seven-year periods.

4.2.3 Results

The results from estimating (4.2), given in Table 4.1, lend mixed support for the polarization hypothesis. While estimates for $\alpha_{MS} < 0$ and $\alpha_{HS} > 0$ have the expected sign, they are not significant when estimated with all the parameters specified in (4.2). However, with just electrical and electronic equipment included in regression, α_{MS} is negative and significant at the 5% level. Column (4) of Table 4.1 suggests that, over a seven-year period, a 10% increase in electrical and electronic equipment capital is associated with a decrease in the wage share of middle-skilled workers of around 0.2, whereas it is associated with a relative increase in the wage share of high-skill workers versus low-skilled workers.

The sign of coefficient estimates for the *software* variable are opposite to that of *equipment*. This suggests a qualitative difference between software capital and equipment capital: perhaps it is a complement to medium-skilled labor? It is certainly the case that many middle-skilled occupations, such as call-center clerks, make heavy use of software capital; this is one possible avenue for future research. Since *equipment* includes telecommunications infrastructure, one interpretation is that *outsourcing*, rather than a direct application of labor-saving capital, is responsible for the decline in middle-skill labor.

These results should be interpreted with caution. Since there is no obvious natural experiment, and nor is there a clear instrument for ICT expenditure, this relationship should be interpreted simply as a correlation. Furthermore, it is unlikely that the level of ICT capital can be considered exogenous, since it is a substitute for endogenously-chosen middle-skilled labor. Nonetheless, the preceding analysis supports the more 'nuanced' view that occupational tasks, rather than other human capital variables, are important determinants of the evolution of the wage distribution.

4.2.4 Discussion

The evidence given above is only informal, although it is highly suggestive of a process of polarization in the Australian work force, consistent with patterns found in other labor markets. The results discussed so far also strongly suggest the simple SBTC story does not explain the evolution of the wage distribution in Australia. To wit, the notion of a 'skill premium' is problematic in that, in this analysis, educational attainment appears to be a poor proxy of an individual's level of 'skill.' Secondly, changes in the distribution of earnings as a result of technological change, appear to depend crucially on the nature of the job, rather than the level of skill it requires that workers possess.

4.3 Tasks and Wages

In the previous two chapters, we have seen that the 'canonical' model of skill-biased technical change does a poor job of explaining the evolution of wage inequality in Australia. In particular, while growing inequality the

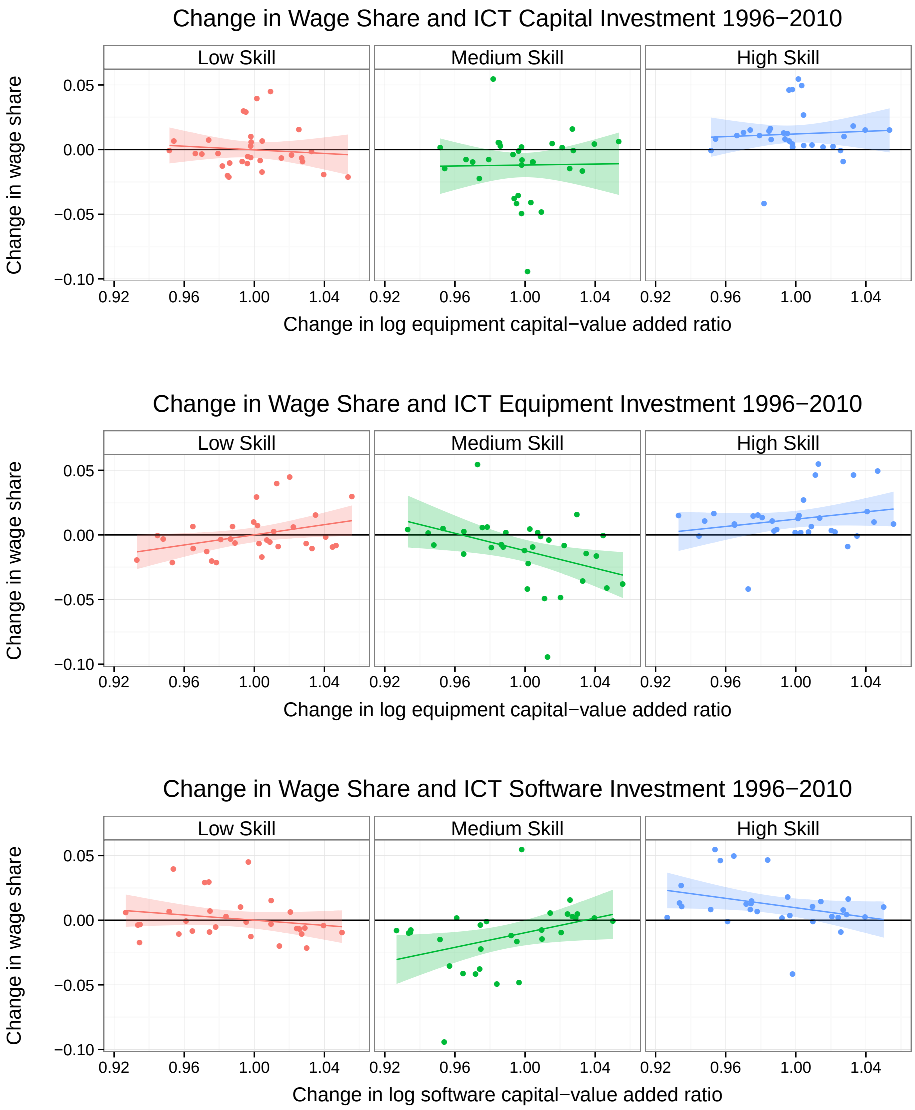

Figure 4.4: Change in wage share against change in: (1) change in log overall ICT capital ratio, (2) change in log ICT electrical and electronic equipment capital ratio, (3) change in log ICT software capital ratio, by industry, Australia, 1996-2010. Fitted line computed using OLS regression with ordinary 95% confidence interval. See note for Table 4.1 for further details. Source: ABS (Survey of Income and Housing and National Accounts).

	Dependent variable:								
	$\Delta SHARE^H$			$\Delta SHARE^M$			$\Delta SHARE^L$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ *ICT capital*	0.045			0.102			−0.147		
	(0.147)			(0.198)			(0.127)		
Δ *Non-ICT capital*	0.236			−0.546*			0.310		
	(0.190)			(0.256)			(0.163)		
Δ *equipment*		0.143			−0.335*			0.191*	
		(0.103)			(0.136)			(0.089)	
Δ *software*			−0.049			0.174*			−0.125*
			(0.059)			(0.078)			(0.048)
Δ *value added*	0.178	0.064	0.030	−0.131	0.081	0.190	−0.047	−0.145	−0.220
	(0.172)	(0.142)	(0.147)	(0.232)	(0.187)	(0.193)	(0.148)	(0.122)	(0.120)
Observations	32	32	32	32	32	32	32	32	32
R^2	0.063	0.067	0.028	0.149	0.179	0.155	0.179	0.179	0.227
Adjusted R^2	-0.037	0.002	-0.039	0.058	0.122	0.097	0.091	0.123	0.174

Note: *p < 0.05; **p < 0.01

Table 4.1: Wage shares computed for full-time workers, whose primary sources of income are wages and salaries, estimated for 16 industry groups. ‘High skill’ workers include professionals and managers, ‘middle skill’ workers include sales persons, clerical workers and para-professionals, and ‘low skill’ workers include jobs with a high degree of manual activity, including laborers, transport workers and trades persons. To smooth out noise, all variables are estimated in seven-year differences. Survey data are composition adjusted by age bracket, sex and education level to be consistent with 2010 demographics. The variables *equipment* and *software* respectively refer to the capital stock of electronic and electrical equipment and computer software, at the end of each period. *other capital* refers to non-ICT capital, and *‘value added’* is the value added for that industry group. Regression intercept omitted. Source: ABS (Survey of Income and Housing and National Accounts).

Australian labor market has mirrored that of overseas economies, there is no empirical evidence that this has been driven by a premium paid to 'educated' workers, relative to less educated workers.

The evidence presented above lend weight to Goos & Manning's (2007) more 'nuanced' interpretation of SBTC. While educational attainment may explain only little between-group inequality, the data seem to suggest an association between occupational affiliation and the widening wage distribution. This explanation suggests that it is specific attributes of these occupations, and not the education required to undertake them, that explains changes in the wage share. Specifically, it is the 'middle-skill' or 'routine' occupations described by Autor et al. (2003) and Goos, Manning, and Salomons (2009) that can be outsourced by firms or automated by investments in labor-saving capital equipment. Under this hypothesis, specific attributes of these jobs allow them to be replaced or outsourced, shifting firms' demand curves for these types of labor to the left. As a result of an excess of supply over demand, wages in these occupations are bid down, and observed wage distributions are both compressed and shifted left.

The analysis presented above (§4.2) relies on a somewhat arbitrary three-way division of occupations, and presents only correlations between the wage share and capital. Further, this statistical correlation cannot establish a causative relationship between the shrinking wage share of middle-income jobs, and a rising capital-output ratio for the industry. Clearly, a more rigorous analysis is required to demonstrate a clear relationship between tangible properties of middle-skilled jobs and falling wages.

For the remainder of this chapter, we aim to present a more rigorous analysis, using data on occupational task content compiled by the US Department of Labor to determine which occupations are likely candidates for automation and offshoring. This data, made available as part of the O*NET database, provides measures of the types of tasks that specific occupations entail. We adapt a procedure developed by Jensen and Kletzer (2010) as an extension to Autor et al. (2003), who use the US Dictionary of Occupational Titles, the predecessor to O*NET, to compile indexes for 'offshorability' and 'routineness.' These indexes provide a quantitative foundation for comparing changes in the wage distribution and occupations at risk of structural change due to the processes of offshorability and routinization.

4.3.1 Data: Occupational Classification Schemes

As with the previous analysis, to bring the models to the data, we obtain unit-level microdata for the Survey of Income and Housing (SIH). Consistent with our previous analysis, we include only full-time or own-account workers. One challenge posed by the SIH is its occupational coding scheme. The scheme used in successive editions of the SIH has changed over time. In the 1981/82 survey, occupations are recorded using the 1976 Census Classification and Classified List of Occupations (CCLO) codes. Occupations in the 2000/01 SIH are coded using the 1996 Australian Standard Classification of Occupations (ASCO), second edition. And the 2011/12 survey is encoded using the 2006 Australian and New Zealand Standard Classification of Occupations (ANZSCO). (A discussion of occupational coding can be found in the appendix, §A.3). In the absence of a consistent classification scheme that permits comparison of the same occupational wage profile in different periods, it is not possible to analyze wage changes by occupation. This challenge is not unique to Australian data: occupational coding systems have changed several times in the post-war era in the United States, for example (see Autor and Acemoglu, 2012; Meyer and Osborne, 2005).

To facilitate comparison, other authors have developed hybrid classification schemes that merged occupations into comparable groups.[3] We take the same approach here, and create two such schemes. The first, comprising 29 hybrid occupations, compares the 1981/82 survey with 2011/12 (Table A.1), and the second, with 28 hybrid occupations, compares 2000/01 and 2011/12 (Table A.2). Firpo et al. (2011) employ a similiar number of hybrid groups (40) in their study of occupational wage changes in the United States between 1988 and 2003. These 'consistent' classification schemes can then be linked to occupational task measures, and compared across time periods.

Unfortunately, data could only be obtained at the minor group (2-digit) level. This means that, compared to overseas studies that were able to employ four-digit data, our results must carry a higher degree of error due to classification mismatches.

4.3.2 Data: Occupational Task Measures

In order to determine whether specific properties of jobs are associated with changes in the occupational wage profiles, quantiative measures of these properties are required. Unfortunately, Australian classification schemes, make only very limited task information is available.[4] This need not be a limitation. Facing a similar deficiency in British and European job classication schemes, Goos, Manning, and Salomons (2009) map local occupation classifications to the US occupational classification scheme in order to exploit the data available in the O*NET. We construct a similar mapping, between the ANZSCO and O*NET at the unit group (four digit) level, and then

[3]See, for example, Autor et al. (2003), Fortin, Lemieux, and Firpo (2011), Acemoglu and Autor (2011).

[4]Some task information, including tasks and knowledge requirements, are available in the ANZSCO and ASCO. Although some quantitative studies have successfully exploited these requirements (Barnes & Kennard, 2002, e.g.), they are not given in a form that can be readily used for quantitative analysis: see the appendix (§B) for a discussion.

weight these data by population for the hybrid occupational classifications. See the appendix (§B.2) for details.

If the routinsation hypothesis is true, then we expect to see a relationship between the 'offshorability' or 'routineness' of a job, and its occupational wage distribution. We thus require indexes for these characteristics for each hybrid occupational group, defined above. One problem with the O*NET database is its sheer size: it contains hundreds of measures, and dozens of different kinds of scales. Jensen and Kletzer (2010) and Firpo et al. (2011) adopt the approach of combining several O*NET indexes to create an aggregate, and we employ Firpo et al's formula for five separate indexes. Three indexes are used as proxies for 'offshoreability': *information content*, *no on-site work* and *no face-to-face contact*. To measure 'routinization,' we have two indexes: *automation/routinization* and *no decision-making*.[5]

Income data were only available at the minor group (two-digit) level, but the occupation indexes we construct are at the occupational group (four-digit) level. We therefore use census data to compute a weighted average for each index, by the number of full-time workers, in each minor group. This has the unfortunate downside of reducing variation in our dataset.

4.3.3 Stylized Facts

Before analyzing changes in occupations over time, we first describe the relationship between task indexes and occupational conditional means using a single cross-section of the data. Figure 4.5 plots the relationship between mean full-time wages, as measured in the 2011 Australian Census of Income and Housing, and the task measures constructed from O*NET data.[6] The

[5] These task indexes are not completely independent. See the appendix (§B.2) for a discussion.

[6] Census data are used in Figure 4.5, rather than the SIH, because occupational wages are available at a greater level of detail: ANZSCO unit groups (four digit), rather than

data are plotted at the ANZSCO unit group (four digit) level, and include a loess regression line, weighted by occupation population. These data are also summarized at the ANZSCO major group level in the appendix, in Table B.1.

Two obvious patterns emerge in Figure 4.5: the information content and decision-making indexes are strongly positively related to conditional mean wages. These relationships are hardly surprising: professional and managerial work, which tends to be relatively highly remunerated, typically involves information processing and a greater degree of decision-making. Similarly, a negative relationship between automation/routinization and conditional mean wages is also evident. As Goos, Manning, and Salomons (2009) argue, so-called 'lovely' jobs, which are usually relatively well-paid, tend to involve primarily nonroutine activities, whereas lower-paid 'middling' jobs tend to involve a greater proportion of repetitive activity. Finally, there does not appear to be a simple relationship between the face-to-face or on-site task indexes.

In order to test the routinization and outsourcing theories of occupational wage change, it is not enough to examine cross sections of the wage distribution at a given point in time. Rather, since our theory posits an increase in wage dispersion as a consequence of technical change, then these changes should be evident over a period of time. That there is a downward-sloping relationship between automation/routinization and conditional wages is insufficient: it must be demonstrated that this relationship is changing over time.

minor groups (two digit). The same chart is replicated using SIH data in Figure B.1; the patterns that emerge are almost identical.

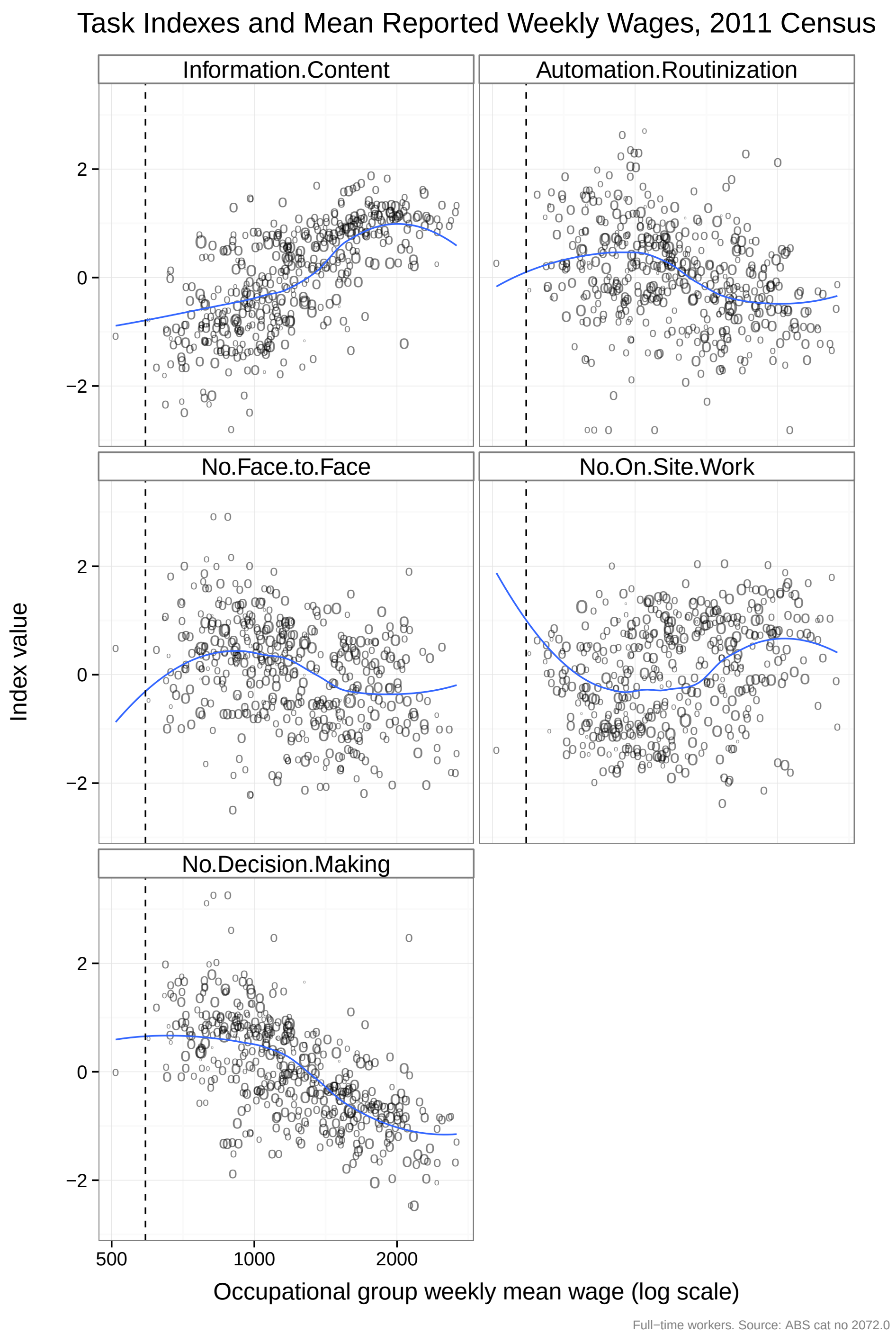

*Figure 4.5: Mean occupational weekly wage and task measure index values, at ANZSCO unit group (4-digit) level. The vertical dashed line is drawn at the level of the National Minimum Wage, of $589.30 per week. Census respondents reporting full-time work are shown. The loess regression line is weighted by population; circle areas are proportional to population for each occupation. Notice that, when occupations are reduced to combined groupings, almost identical trends are observed (c.f. Figure B.1). Sources: ABS cat 2072.0, O*NET, US Dept of Labor.*

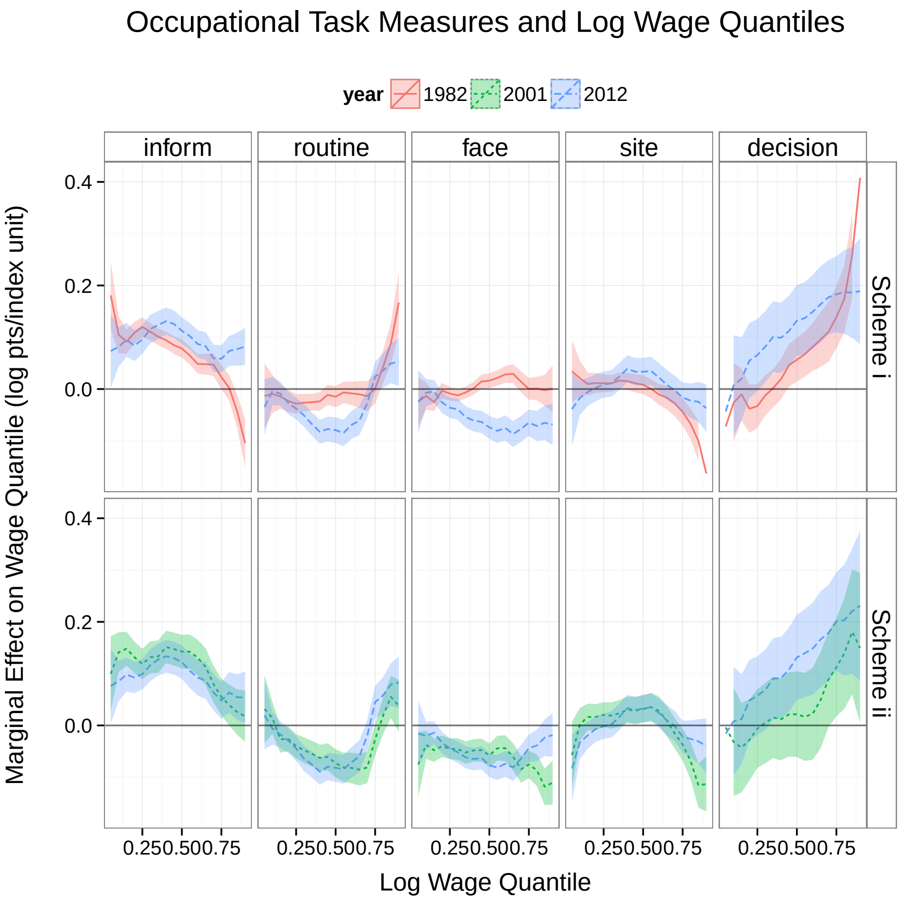

Figure 4.6: Marginal log wage effect of task measures on log wage quantiles, computed with RIF-regressions, 1981/82–2011/12 and 2000/01–2011/12. Shaded areas are 95% analytic confidence intervals. At any given quantile, overlap between the confidence band and the x-axis indicates a lack of statistical significance. The top row shows unconditional quantile regressions against task measures for 1981/82 and 2011/12, and the bottom row, 2000/01 and 2011/12. The vertical axis measures $\partial \ln(w^q)/\partial T_i$*, the marginal impact on the log wage of a unit change of the task measure. Notice the similarity between the 2011/12 curves under both coding schemes. This similarity suggests that occupational coding schemes map consistently to the underlying O*NET task measures. Sources: ABS SIH 1981/82, 2000/01, 2011/12; ABS cat. no. 6401.0, 1220.0, 1223.0, 1288.0.; U.S. Dept of Labor.*

4.4 A Simple Test of the Roy Model

In our simple industry-level analysis of different skill groups (§4.2), we concluded that it was the nature of jobs, rather than the level of 'skill' they required, that mediated the impact of technical change. In this and the following analysis, we attempt to decompose changes in the wage distribution, according to the tasks involved in each job.

The key challenge to arise out of an exercise such as this is identification. As Fortin et al. (2011) point out, if panel data were available that included a longitudinal look at individuals who remained in a single occupation over a long period of time, and the data included a detailed breakdown of the tasks and skills required to do their jobs, then identification would be trivial. Instead, we have only repeated cross-sections of income data, and we must infer task data from occupational titles.

Decomposition methods are especially powerful because they are able to extract relatively rich information from the data. However, this strength comes at the price of strong assumptions imposed on the data in order to guarantee parameter identification; the limitations these assumptions bring are shared by all decomposition methods, and are discussed in detail in section 4.5.1. The strength of these assumptions stem from the fact that decompositions provide only 'shallow', empirical analyses of economic phenomena, and are not able to model 'deep,' structural properties of the labor market. The most important of these restrictions, and possibly the least palatable, is the following. Despite motivating our model with Roy's model, a general-equilibrium framework, the empirical analysis presented below assumes that general equilibrium effects are completely dominated by first-order effects, so that market outcomes in each occupation's labor market depends only on the supply and demand for skills in that occupation.[7] This assumption is questionable: it is quite likely, for example, that a collapse in the demand for labor in one occupation, would cause some workers to change their occupational affiliations, triggering a shift in the supply of labor in other occupations. Nonetheless, this and other assumptions we employ below are standard in the inequality literature (Fortin et al., 2011, p.1). These limitations will be discussed in greater detail, below.

4.4.1 Model

The desired decomposition is a relationship between occupations and their constituent tasks. Roy-type models posit that the wage an individual is paid depends on the skills demanded by that occupation, and the returns to the skills in question. One simple approach to identifying the contribution of each one of a worker's skills to the overall wage, considered by Firpo et al. (2011), is to adapt the simple linearly additive functional form of Welch (1969). Welch assumed that an individual's wage is determined linearly by the individual skills that worker possessed.

Assumption 1 (Linear additivity of returns to skills)**.** *An individual i's wage in occupation j at time t is set according to the sum of the returns r_{jk} to skills k, $k = 1, \ldots, K$ required for that occupation:*

$$w_{ijt} = \theta_{jt} + \sum_{k=1}^{K} r_{jkt} S_{ik} + u_{ijt}, \tag{4.3}$$

Where θ_{jt} is a 'base pay' term, S_{ik} is an occupational skill level, and $u_{ijt} \sim$ i.i.d captures idiosyncratic characteristics of each worker.

[7] Within a general equilibrium framework, this assumption is equivalent to the assumption of diagonal dominance (Arrow & Hahn, 1971, p.233).

This is a strong assumption, which enjoys only limited empirical support. Linear additivity implies that the labor market in each occupation is free of general equilibrium effects arising from changes in other occupational wage structures.

Notice that in (4.3), the returns to skill k are particular to occupation j. This makes intuitive sense: since each individual is endowed with a particular mix of skills, which may not necessarily be useful in that individual's chosen occupation, there is no reason to expect the returns to certain skills to equilibrate across markets. In Roy's example described earlier, fly fishing skills of any level do not earn a return for workers engaged in rabbit hunting.

Following Firpo et al. (2011), we perform two analyses of changes in the occupational wage. The first, outlined below, directly analyses the occupational wage profile as quantiles.

As a first step in the analysis, we directly analyze the relationship between occupational task measures and changes in the aggregate occupational wage profile. Under the maintained assumption that wages are linearly separable, it follows that changes in the occupational returns to a particular skill r_{jk} will be observable in the aggregate wage profile.

Estimating a similar model of wage profiles, Juhn et al. (1993) suggested that, in regressions on occupational wage quantiles, a worker's rank within the wage distribution was a good proxy for that worker's ability. Thus, in aggregate, a fixed quantile effect λ^q across groups could be interpreted as an aggregate measurement of changing returns to ability. We first estimate changes in the wage quantiles, for each occupation j and each quantile q,

$$\Delta w_j^q = a_j + b_j w_{j0}^q + \lambda^q + \epsilon_j^q, \tag{4.4}$$

where λ^q is an estimate of returns to skill at each quantile q. Under the maintained assumption that the returns to skill at each quantile of the wage distribution is independent of the actual occupation, then the parameters a_j and b_j describe the changes in each occupation over the study period.

The next step in the analysis is to decompose these changes according to the task we are interested in. These task measures, defined below, capture the ability to offshore or automate an occupation. Applying the first-step regressions defined above, we are now in a position to test the relationship between changes in occupational wage profiles and task indexes:

$$\hat{a}_j = \gamma_0 + \sum_{h=1}^{K} \gamma_{jh} TC_{jh} + \mu_j, \tag{4.5}$$

$$\hat{b}_j = \delta_0 + \sum_{h=1}^{K} \delta_{jh} TC_{jh} + \nu_j. \tag{4.6}$$

4.4.2 Results

The Roy model outlined above posits that, if the demand for labor of a particular type is shifting to the left, then two changes in the wage distribution should be visible: both mean wages and wage disperson should decrease. To test for these changes in the occupational wage distribution, we fit the model described above for two periods: from 1981/82 to 2011/12, using grouping I, and from 2000/01 to 2011/12, using grouping II. Once we have estimates of the change in mean and dispersion of the occupational wage distribution, we regress both of these measures against task measures for offshoring and routinization. Under the model hypothesized above, we therefore expect to obtain negative coefficient estimates for all five task measures.

Second-stage regression results for the periods 1981/82 to 2011/12 and 2000/01 to 2011/12 are tabulated in Tables 4.2 and 4.3, respectively. In both tables, models 1—3 represent estimation results for (4.5), where the change in mean, a_j^q, is the dependent variable, and models 4—6 represent estimation results for regressions on the slope term b_j^q, specified in (4.6). In models (1) and (4), coefficients associated with both outsourcing and routinizaton are entered together; whereas just outsourcing variables feature in models (2) and (5), and routinization variables in (3) and (6). Importantly, the sign and significance of the estimates in both tables are very similar, despite one dataset spanning 30 years, and the other a little over a decade. This suggests that occupational wage changes captured by the model are relatively recent. For the purposes of our discussion here, we will restrict our attention to Table 4.3, which covers the period 2000/01 to 2011/12. Note that while the sign of the coefficients can be interpreted, since these task measures were compiled from unit-free indexes and then arbitrarily normalized to have a unit range, the scale of the coefficients is aribitrary and has no direct interpretation. In particular, the reader is cautioned against comparing the magnitude of index coefficient estimates; it is not clear that this would be at all meaningful.

Table 4.2 does not present any strong evidence for the routinization hypothesis, but it does suggest some interesting evidence for the outsourcing hypothesis. Estimates for variables thought to be associated with routinization, information content and automation/routinization, are shown in columns (3) and (6). They do not appear to have a consistent effect across the income distribution, and the coefficient estimates are not significantly different from zero. We therefore exclude these variables from further consideration from our model.

The evidence for the routinization and outsourcing theories presented in Table 4.2 is somewhat mixed. As expected, a higher level of routinization in

Table 4.2: Intercept and Slope of Change in Wage Quantiles, 1981/2 - 2011/12

	Dependent variable:					
	A (intercepts)			B (slopes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Information content	0.37		0.15	−0.12		−0.03
	(0.23)		(0.17)	(0.10)		(0.08)
Automation/routinization	−0.39		−0.11	0.20*		0.08
	(0.26)		(0.19)	(0.11)		(0.09)
No face-to-face contact	−0.0002	−0.11		0.02	0.09	
	(0.23)	(0.21)		(0.10)	(0.09)	
No on-site work	0.09	0.36**		−0.07	−0.17**	
	(0.20)	(0.14)		(0.09)	(0.06)	
No decision-making	0.64**	0.28*		−0.33***	−0.19***	
	(0.24)	(0.15)		(0.11)	(0.07)	
Constant	0.51***	0.56***	0.59***	−0.20***	−0.21***	−0.24***
	(0.10)	(0.10)	(0.13)	(0.05)	(0.04)	(0.06)
Observations	28	28	28	28	28	28
R^2	0.49	0.41	0.12	0.57	0.50	0.08
Adjusted R^2	0.38	0.33	0.05	0.47	0.44	0.01
Residual Std. Error	394.16 (22)	407.80 (24)	486.62 (25)	173.56 (22)	179.08 (24)	237.22 (25)
F Statistic	4.27*** (5; 22)	5.50*** (3; 24)	1.72 (2; 25)	5.80*** (5; 22)	7.97*** (3; 24)	1.15 (2; 25)

Note: *p<0.1; **p<0.05; ***p<0.01

Occupational grouping I used, with 28 occupational groups.

Table 4.3: Intercept and Slope of Change in Wage Quantiles, 2000/01 - 2011/12

	Dependent variable:					
	A (intercepts)			B (slopes)		
	(1)	(2)	(3)	(4)	(5)	(6)
Information content	−0.71		−0.23	0.11		0.05
	(0.47)		(0.39)	(0.07)		(0.06)
Automation/routinization	−0.49		−0.35	0.07		0.04
	(0.51)		(0.36)	(0.08)		(0.05)
No face-to-face contact	0.29	−0.11		−0.03	0.03	
	(0.48)	(0.41)		(0.07)	(0.06)	
No on-site work	1.11**	0.79**		−0.16**	−0.11**	
	(0.40)	(0.29)		(0.06)	(0.04)	
No decision-making	0.48	0.69**		−0.09	−0.13**	
	(0.45)	(0.32)		(0.07)	(0.05)	
Constant	3.96***	3.91***	4.15***	−0.60***	−0.59***	−0.63***
	(0.23)	(0.24)	(0.29)	(0.03)	(0.04)	(0.04)
Observations	29	29	29	29	29	29
R^2	0.48	0.38	0.03	0.51	0.41	0.03
Adjusted R^2	0.36	0.31	−0.04	0.40	0.34	−0.04
Residual Std. Error	15.43 (23)	16.09 (25)	19.69 (26)	2.27 (23)	2.38 (25)	3.00 (26)
F Statistic	4.18*** (5; 23)	5.11*** (3; 25)	0.47 (2; 26)	4.73*** (5; 23)	5.84*** (3; 25)	0.41 (2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01
Occupational grouping II used, with 29 occupational groups.

an occupation is associated with a decrease in wages, across all quantiles of the wage distribution. However, automation is also associated with *greater* wage dispersion, not less. Consistent with the theory, the slope terms for 'no on-site work' and 'no decision-making' are both signficiantly negative, so that offsite work and a lack of decision-making are both associated with a decreased dispersion of wages. However, contrary to the theory, estimates for changes in the mean wage are significantly *positive*, the opposite of the sign predicted by the theory. Similarly, the evidence for 'information content' is conflicting: although we expect both the change in mean and dispersion to be negative, the change in dispersion is in fact significantly positive.

4.4.3 Discussion

The results in Table 4.2 stand in contrast to Firpo et al. (2011), who found that, in the United States between 1988 and 2002, three out of the five indexes given here are associated with negative changes in both the mean and dispersion of wages. Indeed the mixed results discussed above suggest a number of possible explanations. First, it is possible that the proposed Roy model is inadequate, and simply does not explain changes in occupational wage profiles. Second, changes in the wage profile may not be uniform across the earnings spectrum, as (4.4) assumes. Finally, it could be that these results are simply an artefact of the occupational mapping or aggregation scheme employed, or structural differences between the United States and Australian labor market.

One major difference with the US labor market that could explain the unexpected increase in these jobs, is the presence of a sizeable minimum wage in Australia. In Figure 4.5, notice that the 2011 National Minimum Wage of $622.30 per week, illustrated by the dashed line, is quite close to the conditional mean wage of some occupations. It is therefore possible that, at some wage levels, changes in the mean or dispersion of wages have very little to do with the properties of the job, but instead are due to institutional factors. Proximity of the wage distribution to the level of the minimum wage suggests that the presence of non-linearities in the relationship between tasks and wages could be important.[8]

4.5 Decomposing Wage Changes

In this final stage of the analysis, we attempt to examine the evidence for a causal link between changes in technology and changes in the wage distribution. First, we use the approach suggested by DiNardo, Fortin, and Lemieux (1996) to perform an aggregate decomposition of wages, separating changes in the wage distribution into a composition effect and a wage structure effect. We then proceed one step further, and attempt to explain the wage structure effect by our technology indexes.

4.5.1 Aggregate Decomposition

The theoretical approach we follow here is sketched in the previous chapter (§3.5.4), and described in detail in DiNardo, Fortin, and Lemieux (1996). Recall that, the goal of decomposition approaches is to separate changes in the wage distribution into two parts:

$$\Delta_O = \Delta_S + \Delta_X,$$

[8]The results presented in Tables 4.2 and 4.3 are robust to the exclusion of subsets of quantiles. In particular, excluding quantiles close to the minimum wage has negligible effect on parameter estimates.

where Δ_X is the composition effect, and Δ_S is the wage structure effect. The composition effect is that part of the wage distribution explained by changes in human capital and demographic variables such as potential experience and educational attainment. The wage structure effect is that part which remains unexplained, and which we assume can be explained by our derived task indexes.

However, before we can proceed with estimation, we must impose further assumptions on our data. First, we require that the support of covariates X is the same for both time periods. In other words, it should not be possible to unambiguously predict which time period an observation belongs to, simply by observing the value of its covariates.

Assumption 2 (Overlapping support)**.** *Let the support of wage setting factors in both periods* $[X', \epsilon']'$ *be* $\mathcal{X} \times \mathcal{E}$*. For all* $[x', e']' \in \mathcal{X} \times \mathcal{E}$*,* $0 < \Pr[T = 0|X = x, \epsilon = e] < 1$*.*

Importantly, Assumption 2 means that the set of occupational titles in both periods must be the same, even though many new types of occupational titles have been created since 1981/82. However, although there might have been large changes within occupational groups, a counterpart for each ANZSCO minor group was readily identified in the 1981/82 classification.

Further, in order to identify the explained and unexplained effects of the covariates, we require that the error term ϵ has the same conditional distribution in both time periods. This is known as the *ignorability* assumption.

Assumption 3 (Ignorability)**.** *For* $T \in \{0, 1\}$*, let* (T, X, ϵ) *have a joint distribution. Then, for all* $x \in \mathcal{X}$*,* ϵ *is independent of* T *given* $X = x$*.*

The above assumptions imply at least one fact that is clearly false: that occupational titles in the first period have the same meaning as occupations in the last period. Although it can be argued that, say, the occupation of 'Lawyer' is largely unchanged between the 1980s and the 2000s, the same cannot be said for certain technical professions. The activities of a 'Surveyor,' for example, has been greatly altered by the introduction of GPS technology and portable computers. However, this problem is mitigated somewhat by aggregating occupations into larger groups; see Firpo et al. (2011) for a discussion.

Results

Figure 4.7 plots results for the aggregate wage decomposition across the wage distribution for the same two comparison periods as before, 1981/82–2009/10 and 2000/01–2009/10. The blue lines indicate overall changes in the log wage distribution over the time period, and bear the familiar 'banana' shape seen in Figure 4.3 (although these charts are not disaggregated by sex.)[9] The green line plots the composition effect, which arises from changes explainable by the work force's observable human capital attributes. And finally, the red line plots the difference between these lines, the wage structure effect, which we attribute to changes in the technological environment over the period.

The left-hand panel spans a period of about 30 years, while the right-hand panel spans just one decade. As expected, wage changes are larger for the 30-year timespan than they are for the shorter period. However, for the longer period, notice that it is the wage structure effect that dominates, whereas between 2000/01 and 2009/10, the composition effect dominates. This suggests that, consistent with findings from studies in the United

[9] Figure 4.7 is weighted to match the 1981/82 covariate distribution, whereas Figure 4.3 is weighted to match 2009/10. Consequently, the charts will not have exactly the same profile.

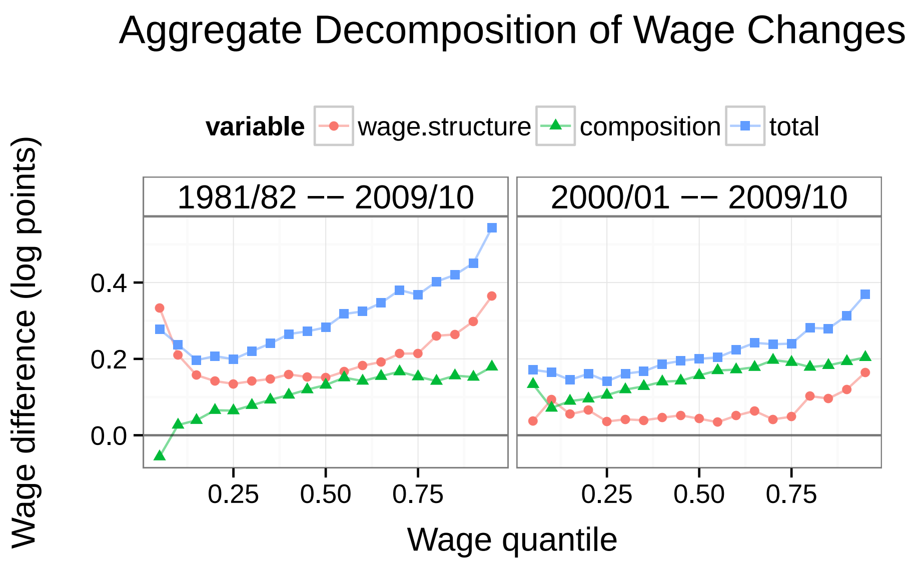

Figure 4.7: Aggregate decomposition of wage changes, 1981/82–2009/10 and 2000/01–2009/10. Due to restrictions in the ABS RADL, confidence intervals could not be computed for this decomposition. Sources: ABS SIH 1981/82, 2000/01, 2009/10; ABS cat. no. 6401.0, 1220.0, 1223.0, 1288.0.; US Dept of Labor.

States and Europe, the technological impact on the wage distribution occured mainly in the 1980s and 1990s.

Notice also that, for the most part, the curves are upward-sloping, especially in the upper three-quarters of the wage distribution. This is consistent with the theories of technical change we have discussed so far, which posit that more 'skilled' workers (here proxied by their position in the wage distribution), benefit more from technical change. However, notice the U-shaped wage structure curve in the left-hand panel: there were significantly greater gains in the lower quartile of the wage distribution than there were in the middle two quartiles. This is a puzzle: perhaps there are other factors that are systematically influencing low-income jobs.[10]

[10]There are many possible explanations for this effect. Since 1981/82, the national minimum wage was introduced. Further, in this study we do not have data on union membership, which has been shown to explain a great deal of changes in the wage distri-

4.5.2 Detailed Wage Structure Decomposition

In order to test the routinization and outsourcing hypothesis, we wish to decompose the wage structure component into contributions from our occupational task indexes. The assumptions stated so far, although sufficient for identifying the wage structure component ($\hat{\Delta}_S$) and endowment effect component ($\hat{\Delta}_X$) of the aggregate decomposition, are insufficient to identify the components of the wage structure.

Fortin et al. (2011, p.27) show that non-parametric estimates of the detailed decomposition require assumptions that cannot be maintained in this context. For example, the 'independence' condition, found in Matzkin (2003), must hold:

Assumption 4 (Independence)**.** *For $T \in \{0, 1\}$, X is uncorrelated with ϵ in time T.*

Most decompositions of the determinants of wages, including this one, follow the Mincerean 'human capital' approach, which suggests that the primary determinants of wages are investments in education and experience, which enhance productivity (J. Mincer, 1962). For that reason, these covariates are included in X in this study. However, as is well-known, OLS regression estimates of Mincer-style wage equations tend to exhibit endogeneity bias, since observable characteristics (such as years of schooling) tend to be correlated with unobserved characteristics such as general ability or talent (Card, 1999). Consequently, any regression specification that omits an accurate measure of 'ability' will exhibit endogeneity bias, since the omitted variable will cause explanatory variables such as schooling to be correlated with the error term. That is to say, the independence property is violated.

bution (Leigh, 2013; Borland, 1996).

However, the impracticality of Assumption 4 can be avoided by imposing the linear functional form in Assumption 1 (Fortin et al., 2011, p.28). Furthermore, the linear functional form assumption allows for heteroskedasticity. In this application, this is a useful property, since income variance increases with educational attainment.

The choice of base case for the detailed decomposition is non-trivial. After experimenting with a number of options, male high school graduates with 15-20 years of potential experience were found to be the base case that yielded the most stable results.

Results

Detailed decomposition results for the wage structure effect, according to our task measure indexes, are shown in Figure 4.8.[11] The chart shows impact a unit change in each variable would have on the log wage, *ceteris paribus*, at quantiles across the wage distribution. A plotted value of zero indicates 'no change'.[12] Points above the x-axis indicate that task measure explains an increase in wage at that quantile, and vice-versa for points below the x-axis.

The decomposition shown in Figure 4.8 demonstrates an important point: the impact of task measures are non-uniform across the skill spectrum. In particular, the impact of decision making is highly variable, depending on the wage quantile. Consider the non-decision-making index in the 1981/82–2009/10 panel. In the 5th percentile, the absence of decision-making is associated with an increase in wages, but a decrease in wages between the 25th

[11]Our detailed decomposition also accounts for potential experience (8 dummies), educational attainment (five dummies), marital status and sex. These variables are not reported.

[12]Due to a restriction in the ABS RADL environment that prohibits looping and the use of the STATA bootstrap facilities, confidence intervals could not be computed for this decomposition. This makes interpreting the results difficult, since statistical significance can't be determined.

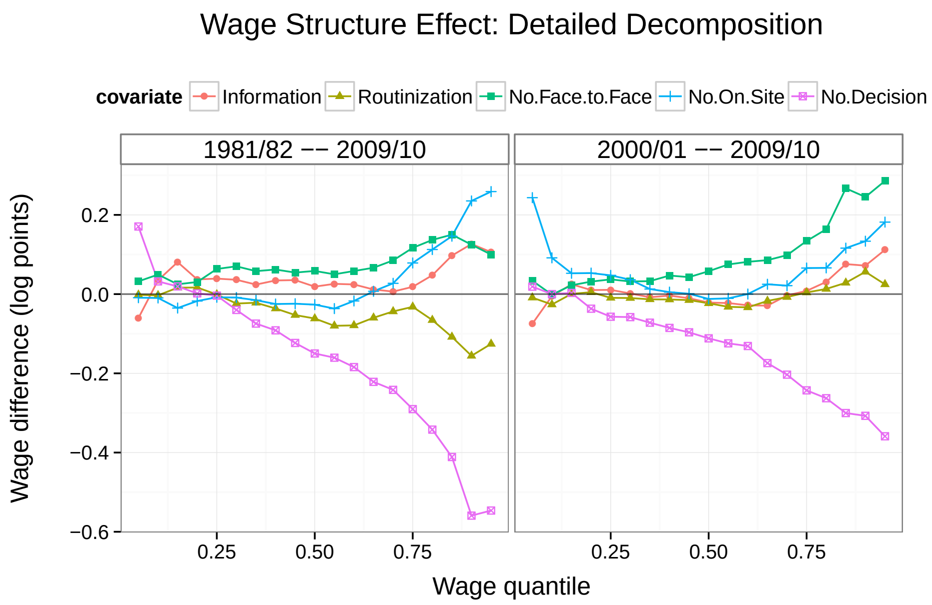

Figure 4.8: Detailed structural decomposition of wage changes, 1981/82–2009/10 and 2000/01–2009/11. Note that, as before, since task indexes are unit-free, direct comparisons between magnitudes of index coefficients is not meaningful. Confidence intervals could not be computed due to restrictions in the ABS RADL. Sources: ABS SIH 1981/82, 2000/01, 2009/10; ABS cat. no. 6401.0, 1220.0, 1223.0, 1288.0.; US Dept of Labor.

and 95th percentiles. Notice that the trend for the (lack of) decision-making variable is very similar in both the 1981/82–2009/10 and 2000/01–2009/10 charts. This suggests that the structural changes that led to the increasing value of management roles for high-income earners occurred over the period of the 2000s.

Figure 4.8 provides evidence for the routinzation hypothesis, but only in the top half of the income distribution. Jobs that involve routine tasks are associated with a negative change in wages between 1981/82 and 2009/10. However, this trend is not present in the most recent decade, suggesting that replacement of routine jobs occurred in the 1980s and 1990s. This is consistent with the findings of Firpo et al. (2011), who find a negative routinzation effect only in the 1980s.

Interpretation of the other variables is somewhat more difficult. In particular, remuneration for jobs with no face-to-face content and an absence of on-site work appears to have grown for higher wage quantiles. These variables, which were included in order to test the 'offshoring' hypothesis, could instead be detecting the rise remuneration for information-economy jobs experienced in the 1990s and 2000s. Although it is true that call center operators do not have to be on a client's site or see them face-to-face in order to do their jobs, the same can be said for a computer programmer, an occupation for which remuneration grew dramatically over the 1990s and 2000s. Indeed, at top wage percentiles, a higher information content is also associated with higher earnings, which does lend weight to this explanation.

4.6 Conclusions

In this chapter, we brought some of the models we considered here to the Australian data. Contrary to the experience of foreign labor markets, but consistent with older Australian studies, we found that the widening income distribution does not appear to being driven by a widening 'college premium,' which casts doubt on the 'canonical' model of SBTC.

We did, however, find support for the theory that the wage share of middle-skill jobs is declining. Consistent with other studies in foreign labor markets, this could be suggestive of firms investing in plant equipment in order to replace certain types of workers. However, this evidence is extremely weak, and can only be treated as a correlation.

Direct tests on the wage structure suggested that there was no simple relationship between the constructed task indexes and the wage structure. Although the change in the dispersion of 'off-shoreable' jobs was significant and in the expected direction for two out of three of the indexes, changes in base wages were generally positive. While it is possible that the minimum wage or other institutional factors rendered this model inappropriate, these results nonetheless demonstrate that the relationship between tasks and wage changes is complex.

Decomposition results suggest that the bulk of structural changes in the wage distribution occurred in the 1980s and 1990s, with wage changes in the 2000s being mostly accounted for by changes in individuals' wage-related variables such as educational attainment and experience.

After eliminating the change that *is* explainable by human capital variables, some evidence for the routinization hypothesis remained: for individuals in the upper three quarters of the wage distribution, routine work was associated with a lower wage in 2009/10 than in 1981/82. However, this structural change appears to have taken place in the 1980s and 1990s, not the 2000s. In the 2000s, we found evidence of the rising value of management tasks in a job, the magnitude of which grows across the income distribution.

Chapter 5

Conclusions & Further Research

5.1 Main Contributions

The main empirical finding in this study is that there is evidence for structural changes in the wage distribution in the 1980s and 1990s, and during the 2000s for the top 10 per cent of workers. In particular, we find some evidence that this structural change is due to technology shifts, and in particular we find limited support for the routinization hypothesis in the 1980s and 1990s. However, consistent with other literature on SBTC, the Australian experience appears to be somewhat different to that of other advanced countries. We also established that the relationship between skill profiles and technical change is not simple: the impact of technical change is quite different in different parts of the income distribution.

This study confirmed and updated the finding that the 'canonical' model does not fit the Australian data particularly well. It does not explain the growing wage inequality observed in the data, even though rising educational attainment suggests that a skill premium should be present. It is also established that the middle-skill wage share appears to be falling, an effect that is expected if the polarization hypothesis is correct, and consistent with the data in overseas economies.

Using the methods outlined in this study, we were not able to find consistent support for the outsourcing hypothesis. This is likely due to inappropriate application of task indexes, rather than evidence that outsourcing has not occurred. However, we did find evidence of rising returns to management activities that emerged mainly over the 2000s.

Finally, one contribution of this study is to establish a detailed set of task measures that can be used with Australian occupational codings, based on the US O*NET database.

5.2 Limitations

The main limitation of this research is its use of income survey data that are not consistently coded over the entire study period. Australian occupational codings have changed relatively frequently, which makes consistent comparisons of wage profiles over time especially difficult. The construction of synthetic composite occupational classifications is an imperfect way to work around this problem, since the synthetic groups are at best only approximately comparable.

One further challenge presented by the available data is that, for privacy reasons, detailed income surveys from the 1980s and 1990s do not provide detailed occupational codings. Unfortunately, this is exactly the period when structural change appears to have occurred; without better data, it will not be possible to identify with greater precision the periods in which technical change altered the wage distribution.

Our approach observed only a limited subset of changes to the wage distribution. By assuming that the work activities involved in each occupation remained static over the entire study period, we were only able to study changes in tasks between occupations, rather than within them. More detailed task measures—and in particular, a task time series—would be helpful in addressing this limitation in future work.

Furthermore, for simplicity, this study only addressed full-time employees and workers of own account, in order to ensure a consistent comparison of tasks between periods. The rise of part-time work is an important trend in the Australian labor market, and likely to be linked to skill and activity changes (see Esposto, 2012). The inclusion of work hours in the study, which we were able to ignore by studying only full-time workers, would broaden the study to include under-employment for low-skill and casual workers (Briggs, Buchanan, & Watson, 2006).

5.3 Suggestions for Further Research

The findings in this study suggest that a more detailed examination of task-level phenomena in the Australian labor market would be fruitful. A wide range of wage surveys are available, and we have employed only one in this study. A number of alternative data sources stand out. These include the Employee Earnings, Benefits and Trade Union Membership (EEBTUM) survey, available in various forms since the mid-1970s. EEBTUM would be useful because it includes not just occupational information, but also data on union membership, a variable linked to profound structural wage changes over the past 30 years. Another alternative is the Household Income and Labour Dynamics in Australia (HILDA) survey. HILDA would also be useful, even though it covers only the 2000s, because occupational data in its early years have been re-coded to be consistent since the introduction of the new ANZSCO occupational coding scheme in 2006.

As mentioned above, the use of only part-time workers excludes a large and important part of the work force. Further research that considers the relationship between technical change and part-time work would be helpful, especially since part-time workers are relatively likely to be in routine or offshoreable occupations.

Finally, the task measures used in this study employed only a small fraction of the data available in the O*NET database. The results obtained in task decompositions suggest that managerial work is an important component of structural wage changes; perhaps task measures could be constructed that examine this trend in more detail.

5.4 Final Remarks

This study was motivated by a desire for a better understanding of factors that determine workers' wages, and in particular, the way in which technology has altered those factors. Advances in technology have undoubtedly created countless opportunities for workers over many centuries, and there is little doubt about its benefits. Yet it is also disruptive, and it imposes heavy costs on incumbents whose skills have been rendered obsolete by the latest technological advance. The 'creative destruction' of technological change can be an unpredictable, devastating force on workers livelihoods; a better understanding of where it might strike is valuable information.

In this study, we have learned that many of today's routine jobs are likely to face competition from capital equipment tomorrow, with unfortunate consequences for workers. We also found that roles without a decision-making component face increasing penalties further up the wage distribution. These are important facts to inform education policy, and valuable guidance for those facing career choices now that will affect their lifetime earnings.

Moreover, if humans and capitals are, in some sense, complements in production, then a better allocation of people and machines to roles will surely have benefits for everyone. Rather than perceive technology as some kind of invading force on routine jobs, perhaps recent technological change should instead be viewed as a shift in the optimal mix of capital and labor, that will lead to a more productive, wealthier society?

Bibliography

ABS. (2013a). 5206.0 - Australian National Accounts: National Income, Expenditure and Product, Dec 2012. Canberra: Australian Bureau of Statistics.

ABS. (2013b). 6202.0 Labour Force Survey - April 2013. Canberra: Australian Bureau of Statistics.

Acemoglu, D. (2003, March). Labor- and Capital-Augmenting Technical Change. *Journal of the European Economic Association*, *1*(1), 1–37

Acemoglu, D., & Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics, volume 4, part b* (Chap. 12, Vol. Volume 4, pp. 1043–1171). Elsevier

Arrow, K. J., & Hahn, F. H. (1971). *General competitive analysis*. Holden-Day San Francisco.

Atkinson, A. B., & Leigh, A. (2013, June). The Distribution of Top Incomes in Five Anglo-Saxon Countries Over the Long Run. *Economic Record*, *89*, 31–47

Atkinson, A. B. (1997). Bringing income distribution in from the cold. *The Economic Journal*, *107*(441), 297–321.

Autor, D. H. (2013). The 'task approach' to labor markets: an overview. *Journal for Labour Market Research*, 1–15

Autor, D. H., & Acemoglu, D. (2012). *Skills, Tasks and Technologies Beyond the Canonical Model.*

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *National Bureau of Economic Research Working Paper Series*, *No. 11986*.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in US wage inequality: Revising the revisionists. *The Review of Economics and Statistics*, *90*(2), 300–323.

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998, November). Computing Inequality: Have Computers Changed the Labor Market? *The Quarterly Journal of Economics*, *113*(4), 1169–1213

Autor, D. H., Levy, F., & Murnane, R. J. (2002, April). Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank. *Industrial and Labor Relations Review*, *55*(3), 432–447

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Barnes, P., & Kennard, S. (2002). Skill and Australia's productivity surge.

Barón, J. D., & Cobb-Clark, D. A. (2010, June). Occupational Segregation and the Gender Wage Gap in Private- and Public-Sector Employment: A Distributional Analysis*. *Economic Record*, *86*(273), 227–246

Beaudry, P., & Green, D. A. (2005, July). Changes in U.S. Wages, 1976–2000: Ongoing Skill Bias or Major Technological Change? *Journal of Labor Economics*, *23*(3), 609–648

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education.* University of Chicago Press.

Berman, E., Bound, J., & Griliches, Z. (1994). Changes in the demand for skilled labor within US manufacturing: evidence from the annual survey of manufactures. *The Quarterly Journal of Economics*, *109*(2), 367–397.

Berman, E., Bound, J., & Machin, S. (1998, November). Implications of Skill-Biased Technological Change: International Evidence. *The Quarterly Journal of Economics*, *113*(4), 1245–1279

Blinder, A. S. (1973, October). Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, *8*(4), 436–455

Borland, J. (1996, June). Union Effects on Earnings Dispersion in Australia, 1986–1994. *British Journal of Industrial Relations*, *34*(2), 237–248

Borland, J. (1999). Earnings inequality in Australia: changes, causes and consequences. *Economic Record*, *75*(2), 177–202.

Borland, J., Hirschberg, J., & Lye, J. (2004, September). Computer knowledge and earnings: evidence for Australia. *Applied Economics*, *36*(17), 1979–1993

Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, *117*(1), 339–376.

Briggs, C., Buchanan, J., & Watson, I. (2006). *Wages policy in an era of deepening wage inequality.* Academy of the Social Sciences in Australia.

Brynjolfsson, E., & McAfee, A. (2011). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy.*

Cain, P. S., & Treiman, D. J. (1981, June). The Dictionary of Occupational Titles as a Source of Occupational Data. *American Sociological Review*, *46*(3), 253–278

Card, D. (1999). The causal effect of education on earnings. In O. C. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Chap. 30, Vol. Volume 3, pp. 1801–1863). Elsevier

Card, D., & DiNardo, J. E. (2002, October). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics*, *20*(4), 733–783

Card, D., Lemieux, T., & Riddell, W. (2004). Unions and wage inequality. *Journal of Labor Research*, *25*(4), 519–559

Castles, I. (1986). *Australian standard classification of occupations: Statistical classification.* Australian Bureau of Statistics.

Coelli, M., & Wilkins, R. (2009, September). Credential Changes and Education Earnings Premia in Australia. *Economic Record*, *85*(270), 239–259

Costinot, A., & Vogel, J. (2010, August). Matching and Inequality in the World Economy. *Journal of Political Economy*, *118*(4), 747–786

Cully, M. (1999). *More or less skilled workforce?: changes in the occupational composition of employment, 1993 to 1999.* National Institute of Labour Studies. Adelaide, South Australia: National Institute of Labour Studies.

Davis, E. (2009, November). The ACTU Congress of 2009. *Labour History*, (97), 169–183

Davis, S. J., & Haltiwanger, J. (1991). Wage Dispersion Between and Within U.S. Manufacturing Plants, 1963-1986. *National Bureau of Economic Research Working Paper Series*, *No. 3722.*

de Laine, C., Laplagne, P., & Stone, S. (2001). *The increasing demand for skilled workers in Australia: the role of technical change*, Productivity Commission Staff Research Paper, AusInfo. Canberra.

DiNardo, J. E., Fortin, N. M., & Lemieux, T. (1996, September). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semi-parametric Approach. *Econometrica*, *64*(5), 1001–1044

DiNardo, J. E., & Pischke, J. (1997). The returns to computer use revisited: Have pencils changed the wage structure too? *The Quarterly Journal of Economics*, *112*(1), 291–303.

Dixit, A. K. (1994). *Investment under uncertainty.* Princeton university press.

Esposto, A. (2012). Upskilling and polarisation in the Australian labour market: a simple analysis. *Australian Bulletin of Labour*, *37*(2), 191–216.

Esposto, A., & Abbott, M. (2011, September). A Look at the Long-term Accumulation of Human Capital and Knowledge Intensity of Work in Australia. *Economic Papers: A journal of applied economics and policy*, *30*(3), 414–430

Esposto, A., & Garing, A. (2012, September). The Worker Activities of Australian Employees. *Economic Papers: A journal of applied economics and policy*, *31*(3), 346–358

Firpo, S., Fortin, N. M., & Lemieux, T. (2009, May). Unconditional Quantile Regressions. *Econometrica*, *77*(3), 953–973

Firpo, S., Fortin, N. M., & Lemieux, T. (2011). *Occupational tasks and changes in the wage structure*, Institute for the Study of Labor.

Fortin, N. M., Lemieux, T., & Firpo, S. (2011). Decomposition Methods in Economics. In D. Card & O. Ashenfelter (Eds.), *Handbook of labor economics* (Chap. 1, Vol. Volume 4, pp. 1–102). Elsevier

Freeman, R. B. (1994). How Much Has De-Unionization Contributed to the Rise in Male Earnings Inequality? In S. Danziger & P. Gottschalk (Eds.), *Uneven tides* (p. 133). Russell Sage Foundation.

Friedberg, L. (2003). The Impact of Technological Change on Older Workers: Evidence from Data on Computer Use. *Industrial and Labor Relations Review*, *56*(3), 511–529.

Gaston, N., & Rajaguru, G. (2009, September). The Long-run Determinants of Australian Income Inequality. *Economic Record*, *85*(270), 260–275

Goldin, C., & Katz, L. F. (1998, August). The Origins of Technology-Skill Complementarity. *The Quarterly Journal of Economics*, *113*(3), 693–732.

Goldin, C., & Katz, L. F. (2007). Long-Run Changes in the U.S. Wage Structure: Narrowing, Widening, Polarizing. *National Bureau of Economic Research Working Paper Series*, *No. 13568*.

Goos, M., & Manning, A. (2007, February). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics*, *89*(1), 118–133

Goos, M., Manning, A., & Salomons, A. (2009, May). Job Polarization in Europe. *American Economic Review*, *99*(2), 58–63.

Griliches, Z. (1969). Capital-skill complementarity. *The review of Economics and Statistics*, *51*(4), 465–468.

Harding, A. (1997). The suffering middle: Trends in income inequality in Australia, 1982 to 1993–94. *Australian Economic Review*, *30*(4), 341–358.

Heckman, J. J., & Taber, C. (2008). Roy model. In S. N. Durlauf & L. E. Blume (Eds.), *The new palgrave dictionary of economics*. Basingstoke: Palgrave Macmillan.

Jensen, J. B., & Kletzer, L. G. (2010). Measuring tradable services and the task content of offshorable services jobs. In *Labor in the new economy* (pp. 309–335). University of Chicago Press.

Johnson, G. E. (1997, April). Changes in Earnings Inequality: The Role of Demand Shifts. *The Journal of Economic Perspectives*, *11*(2), 41–54

Juhn, C., Murphy, K. M., & Pierce, B. (1993, June). Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy*, *101*(3), 410–442

Karoly, L. A. (1992, February). Changes in the Distribution of Individual Earnings in the United States: 1967-1986. *The Review of Economics and Statistics*, *74*(1), 107–115

Katz, L. F., & David, H. (1999). Changes in the wage structure and earnings inequality. *Handbook of labor economics*, *3*, 1463–1555.

Katz, L. F., & Revenga, A. L. (1989, December). Changes in the structure of wages: The United States vs Japan. *Journal of the Japanese and International Economies*, *3*(4), 522–553

Katz, & Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics*, *107*, 35–78.

Krueger, A. B. (1993, February). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989. *The Quarterly Journal of Economics*, *108*(1), 33–60

Leigh, A. (2005). Deriving Long-Run Inequality Series from Tax Data. *Economic Record*, *81*(s1), S58–S70.

Leigh, A. (2013). *Battlers & Billionaires: The Story of Inequality in Australia*. Redback Series. Black Incorporated.

Levy, F., & Murnane, R. J. (1996, May). With What Skills Are Computers a Complement? *The American Economic Review*, *86*(2),

Mankiw, N. G., Romer, D., & Weil, D. N. (1992, May). A Contribution to the Empirics of Economic Growth. *The Quarterly Journal of Economics*, *107*(2), 407–437

Matzkin, R. L. (2003, September). Nonparametric Estimation of Nonadditive Random Functions. *Econometrica*, *71*(5), 1339–1375

Meyer, P. B., & Osborne, A. M. (2005). *Proposed category system for 1960-2000 Census occupations*. US Department of Labor, Bureau of Labor Statistics, Office of Productivity and Technology.

Michaels, G., Natraj, A., & Reenen, J. V. (2013). Has ICT polarized skill demand? Evidence from eleven countries over 25 years. *Review of Economics and Statistics*, *In press.*

Mincer, J. (1962). On-the-job training: Costs, returns, and some implications. *The Journal of Political Economy*, *70*(5), 50–79.

Mincer, J. A. (1974). Schooling and earnings. In *Schooling, experience, and earnings* (pp. 41–63). Columbia University Press.

Mitchell, D. J. B. (1989, January). Wage Pressures and Labor Shortages: The 1960s and 1980s. *Brookings Papers on Economic Activity*, *1989*(2), 191–231

Murphy, K. M., & Welch, F. (1992, February). The Structure of Wages. *The Quarterly Journal of Economics*, *107*(1), 285–326

Nordhaus, W. D. (2007). Two Centuries of Productivity Growth in Computing. *The Journal of Economic History*, *67*(01), 128–159.

Oaxaca, R. (1973, October). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review*, *14*(3), 693–709

Ricardo, D. (1819). *The principles of political economy and taxation* (E. C. K. Gonner & Q. Li, Eds.). World Scientific.

Richardson, S., & Harding, A. (1999). Poor workers? The link between low wages, low family income and the tax and transfer systems. *Reshaping the Labour Market: Regulation, Efficiency and Equality in Australia. Cambridge University Press, Cambridge*, 122–158.

Roy, A. D. (1951, June). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers.* New Series, *3*(2),

Smith, A. (1776). The Wealth of Nations, 1910 ed. *Everyman's Library, London.*

Solow, R. M. (1957, August). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, *39*(3), 312–320

Tinbergen, J. (1974). Substitution of Graduate by Other Labour. *Kyklos*, *27*(2), 217–226.

Tinbergen, J. (1975). Recent research. In *Income differences* (Chap. 2). Amsterdam: North-Holland.

Trewin, D. J., & Pink, B. N. (2006). *ANZSCO: Australian and New Zealand Standard Classification of Occupations.* Australian Bureau of Statistics/Statistics New Zealand.

Welch, F. (1969, July). Linear Synthesis of Skill Distribution. *The Journal of Human Resources*, *4*(3), 311–327

Wooden, M. (2000). The Changing Skill Composition of Labour Demand. *Australian Bulletin of Labour*, *26*(3), 191–198.

Appendix A

Income Surveys

Measures of income are drawn from two principal data sources, both provided by the ABS. The first is the Survey of Income and Housing, a detailed sample survey of household income dynamics, and the second is the Census of Population and Housing, a five-yearly survey of the full Australian population.

A.1 Survey of Income and Housing, 1981-2012

The Survey of Income and Housing (SIH) is a hierarchical, clustered sample survey of income and expenditure patterns of the Australian population, periodically conducted by the Australian Bureau of Statistics. It was first conducted in the 1981-2 fiscal year, followed by 1985-6, and then every two or three years from 1994-5. Microdata files were obtained as confidentialized unit record files (CURFs) for the surveys performed in 1981-2, 1985-6, 1994-5, 1995-6, 1996-7, 1997-8, 2000-1, 2002-3, 2005-6, 2007-8 and 2009-10.

Unlike the Census of Population and Housing, a population survey, the SIH is conducted on just a sample of the population, and unit records are weighted by demographic variables in order to create a representative sample. Weights are produced at three levels of the survey hierarchy: household, income unit and person. (In addition, the SIH is occasionally produced simultaneously with the Housing Expenditure Survey, or HES, in which case further expenditure levels are recorded.) For the purposes of this project, only individual-level records are of interest, and so all estimators are weighted by person weight.

Surveys were accessed using the ABS Remote Access Data Laboratory (RADL), a service that provides access to sensitive data by allowing users to run statistical queries remotely. The RADL allows scripts to contain an extremely limited subset of STATA commands. For privacy reasons, the RADL does not permit the use of boostrapping techniques. Furthermore, all looping features of the STATA language have been removed, so bootstrap estimators cannot be computed manually. For this reason, limited on-premises access was arranged to query the data without limitations.

A.2 Survey Weights & Replication Weights

In all versions of the SIH, the $PERS\_WT$ variable for the ith record is computed as the reciprocal of that individual's probability of selection π_i, where $PERS\_WT_i = 1/\pi_i$. $PERS\_WT_i$ can be interpreted as the number of individuals in the whole population 'represented' by record i. The sum of the inverse selection probabilities is therefore identically equal to the size of the population. Note that, since the π_i refers to the probability of individual i being drawn from the overall population (and not from the sample), the selection probabilities π_i, $i = 1, \cdots, n$, will not sum to 1.

Since bootstrapping techniques are not available, delete-a-group jackknife replication weights are made available for the surveys conducted since 1986, and the 1981/82 survey does not have replication weights. The RADL makes available basic procedures for computing standard errors using these weights.

A.3 Occupational Coding Schemes

In major surveys such as the SIH and Census, respondents' occupations are coded according to standard occupational classification schemes. One major drawback of the SIH is that, over its 30 year history, several distinct and incompatible occupational coding schemes have been used. In particular, the classification schemes for the available editions of the survey are:

1. 1981/82: occupations are coded using the CCLO.
2. 1985/86, 1994/95: occupations are coded using ASCO version 1, at the major group level.
3. 1995/96 to 1997/98: occupations are coded using ASCO version 2, at the major group level.
4. 2000/01 to 2002/03: occupations are coded using ASCO version 2, at the minor group level.
5. 2007/8 to 2011/12: occupations are coded using ANZSCO, at the minor group level.

Revisions to occupational classification schemes are conducted from time to time by statistics bureaus in response to changing reporting requirements, and also to keep with changes in the composition of the work force over time. As new schemes are introduced, such as the ASCO II (Castles, 1986) and the ANZSCO (Trewin & Pink, 2006), link tables are usually produced in order to convert statistical data tabulated using the previous coding scheme to the new scheme. Indeed, detailed link tables are available for both the ANZSCO and ASCO II, and provide a detailed mapping between both schemes. Unfortunately, however, link tables are generally constructed at the finest-grained level of the occupational classfication. In the case of the ANZSCO and both editions of the ASCO, occupational groupings at the minor group (two-digit) level cannot be cleanly mapped from one classification scheme to the other. One occupational group in the ANZSCO might map to several occupational groups in the ASCO II, and vice-versa.

One solution to the problem of incompatible groupings is to create a hybrid classification scheme by pooling occupational super-groups. Although this approach is not perfect—occupational groupings are complex, and a perfect hybrid classification scheme is unlikely to be possible—it does allow a good approximate comparison of occupational wage profiles over time. In this project, a comparison was required between two pairs of periods: 1981/82 and 2011/12 and 2000/01 and 2011/12. Unfortunately, the CCLO, ASCO II and ANZSCO are all sufficiently different, that a hybrid scheme that could accommodate all three periods would have to include very few, very large groups of occupations, reducing the sensitivity of the analysis considerably. Therefore, two schemes were designed, `COMBINEDI` for comparing 1981/82 and 2011/12 (Table A.1), and `COMBINEDII` for comparing 2000/01 and 2011/12 (Table A.2). One advantage of maintaining two separate hybrid classification schemes, is that the different schemes serve as an empirical check on the analysis procedure. Despite the different aggregation schemes, similar results should be obtained from both schemes.

The schemes were manually compiled using an iterative procedure. First, fine-grained occupations which comprise each occupational group code in each classification scheme were obtained from (Castles, 1986) and (Trewin

& Pink, 2006). Then, the corresponding occupational group in the other scheme was identified, by going through its occupations. If a group in one scheme mapped to multiple groups in the other, then the groups were deemed to be inseperable, and were merged together in the hybrid classification. Records with no or unknown occupations were simply dropped, as were occupations within the armed forces.

A.3.1 Educational Attainment

Each cross-section includes slightly different educational attainment classifications: some surveys separate graduate from bachelor degrees, some surveys do not record whether respondents graduated from high school. We therefore create two, separate groups: those with bachelor degrees and above, and everyone else. Experiments with other classifications (including excluding trade qualifications) changed estimates somewhat, but did not alter overall trends.

A.3.2 Sources of Income

A number of different coding schemes are given for respondents' principal source of income. We include two groups of workers: employees whose principal source of income comes from their employer, and workers of own account, who may derive income from an unincorporated business. All employee income was included, including tips, overtime, superannuation and bonuses; likewise, all unincorporated business income was included. Other types of income, such as government transfers, revenue from investment, and cash transfers were excluded.

Group	Occupation Title	CCLO Codes	ANZSCO Codes
1	Other managers	12	10, 13, 22, 51
2	CEOs, general managers, Legislators	2	11
3	Health professionals	3–5	25, 41
4	Professionals NFD	10	20, 26
5	Teachers	6	24
6	Legal Professionals	7	6
7	Designers, Engineers, Scientists, Transport Professionals	1, 2, 23, 37	23
8	Technicians	9	30, 31
9	Road transport & railway workers	24, 28-30, 32	73
10	Electrotechnology and Telecommunications trades workers	31,39	34
11	Office support, clerical and postal workers	14, 15, 25, 26	50, 52–56, 59
12	Farmers/farm managers	19	12
13	Farm/rural/garden workers	20, 21	84
14	Storepersons, freight handlers	50	74
15	Labourers	51	80, 82, 89
16	Construction trades workers	41, 43	33
17	Food trades workers	45	35, 85
18	Arts and media professionals	8, 42, 59	21
19	Hospitality workers	54	14, 43
20	Other technicians and trades workers	33–35, 44, 46, 47, 56	36, 39
21	Sales representatives and agents	16, 17	61
22	Sales assistants and support workers	13, 18	60, 62, 63
23	Automotive and Engineering trades workers	36, 38, 40	32
24	Cleaners and caretakers	53, 55, 57	42, 81
25	Sports and personal service workers	58, 60	40, 45
26	Factory process workers	48	83
27	Protective service workers	52	44
28	Machine operators	49	70, 71, 72

Table A.1: The `COMBINEDI` *mapping, at the two-digit level, between the 1976 Census Classification and Classified List of Occupations (CCLO) and the 2006 Australian and New Zealand Standard Classification of Occupations (ANZSCO). This classification is used to compare the 2000/01 and 2011/12 ABS surveys of income and housing.*

Group	Hybrid Occupation Group Title	ASCO II Codes	ANZSCO Codes
1	General Managers, Legislators	10, 11	10, 11
2	Farm Managers	13	12
3	Specialist Managers	12	13
4	Hospitality and Service Managers and Workers	33	14
5	Other Professionals	20	20, 21
6	Business, ICT Professionals	22	22, 26
7	STEM Professionals	21	23
8	Education Professionals	8	24
9	Health Professionals	9	25
10	Sales supervisors and agents	40, 49	61
11	Legal Professionals	25	27
12	Technicians	31	30, 31
13	Auto and engineering tradespersons	41, 42	32
14	Construction tradesworkers	44	33
15	Electricians and telecom tradesworkers	43	34
16	Food trades workers	45	35
17	Skilled Animal and Horticultural Workers	46	36
18	Associate Professionals	30, 39, 63, 83	39, 44, 45
19	Clerical Workers	50, 60, 61, 81	50, 53–56
20	Business and Administration Associate Professionals	32	42, 51
21	Personal Assistants and Secretaries	51	52
22	Other Clerical and Administrative Workers	59	59
23	Sales workers	80, 82	60, 62, 63
24	Plant operators	70	70, 71, 72
25	Road and rail drivers	70–72	73
26	Other production workers	79	74, 83
27	Labourers	90,92,99	80, 82, 84, 85, 89
28	Cleaners	91	81
29	Health and Welfare Support Workers	34	40, 41

Table A.2: The `COMBINEDII` *mapping, at the two-digit level, between the 1996 Australian Standard Classification of Occupations, 2nd Edition (ASCO II) and the 2006 Australian and New Zealand Standard Classification of Occupations (ANZSCO). This classification is used to compare the 1981/82 and 2011/12 ABS surveys of income and housing.*

	ASCO II Major Groups / ANZSCO Major Groups	Managers	Professionals	Technicians, Trades	Community, Personal Service	Clerical and Admin	Sales	Operators and Drivers	Labourers
1	Managers and Administrators	97.65	2.34	0.01	0.00	0.00	0.00	0.00	0.00
2	Professionals	0.82	97.61	0.15	1.31	0.06	0.05	0.01	0.00
3	Associate Professionals	35.45	7.39	20.43	12.78	17.77	6.18	0.00	0.00
4	Tradespersons and Related Workers	0.18	0.01	96.76	1.72	0.09	0.00	0.65	0.60
5	Advanced Clerical and Service Workers	0.00	0.00	0.53	2.72	92.32	4.43	0.00	0.00
6	Intermediate Clerical, Sales and Service Workers	0.02	0.01	0.82	35.75	52.67	10.34	0.00	0.38
7	Intermediate Production and Transport Workers	0.00	0.00	0.18	0.02	3.07	0.09	80.71	15.93
8	Elementary Clerical, Sales and Service Workers	0.00	0.00	0.16	7.33	8.28	76.34	0.33	7.56
9	Labourers and Related Workers	0.00	0.00	0.00	0.03	0.00	0.00	0.02	99.95

Table A.3: Link table between ASCO II and ANZSCO encoding schemes, at the major group level. Weightings reflect population surveyed in 2006 Census of Population and Housing. Source: ABS cat. 1232.0.

Appendix B

Task Measure Construction

One step which was skipped over in the first informal analyses (§4.2) was the assignment of occupations into task groups, on the basis of the occupational classification scheme. If task content is to be analyzed rigorously, and in greater detail than a simple three-occupation breakdown, a quantitative view of occupational task content is required.

B.1 Australia & New Zealand Standard Classification for Occupations (ANZSCO)

The standard classification scheme for occupations used in Australia, ANZSCO, simply lists by name the tasks a particular job title might be required to perform. These tasks are listed in an occupation-specific way, such that they cannot be compared between occupations. For example, under the unit group 2243: *Economists*, the required tasks include

> *Analysing interrelationships between economic variables and studying the effects of government fiscal and monetary policies, expenditure, taxation and other budgetary policies on the economy and*

> *the community (Trewin & Pink, 2006, p. p.185)*

Statisticians (unit group 2441) perform tasks that are largely similar to that of economists, even though the underlying theory that motivates their work may be somewhat different. A corresponding task entry for statisticians includes

> *Defining, analysing and solving complex financial and business problems relating to areas such as insurance premiums, annuities, superannuation funds, pensions and dividends (Trewin & Pink, 2006, p.181)*

Given the qualitative nature of this classification scheme, there is no obvious way to systematically formalize the similarity between economists and statisticians on the basis of the ANZSCO classification. However, alternative classification schemes do exist which include comparable task classifications.

B.2 Occupational tasks: O*NET

The US equivalent to the ANZSCO classification, the O*NET database, includes hundreds of quantitative scales for the level of work activities, knowledge types and abilities for individuals in each of approximately five hundred occupations. The data were constructed using expert surveys, and provide a very rich source of information about the activities that workers in each occupation actually undertake. For example, for the work activity *analyze data*, the occupations *economist* and *surgeon* score highly (6.58/7 and 5.49/7, respectively.) But for the work activity *Handle moving objects*, surgeons score 3.62/7, and economists score only 0.54/7.

We have mapped the ANZSCO (and its predecessors, various editions of ASCO and the CCLO) to the O*NET data, and sucessfully constructued a skill measure series for Australian occupational classification schemes. We then apply a transformation step, described by Firpo et al. (2011), to build composite indexes for 'automation,' 'offshorability', and so on. These composite indexes provide a dependent variable which, along with levels of capital investment on an industry-by-industry basis, provide a basis by which changes in the occupational wage structure can be analyzed. The following five composite indexes are constructed for each occupation code:

A. Characteristics linked to Technological Change/Offshorability

1. Information Content
    - 4.A.1.a.1 Getting Information (JK)
    - 4.A.2.a.2 Processing Information (JK)
    - 4.A.2.a.4 Analyzing Data or Information (JK)
    - 4.A.3.b.1 Interacting With Computers (JK)
    - 4.A.3.b.6 Documenting/Recording Information (JK)
2. Automation/Routinization
    - 4.C.3.b.2 Degree of Automation
    - 4.C.3.b.7 Importance of Repeating Same Tasks
    - 4.C.3.b.8 Structured versus Unstructured Work (reverse)
    - 4.C.3.d.3 Pace Determined by Speed of Equipment
    - 4.C.2.d.1.i Spend Time Making Repetitive Motions

B. Characteristics linked to Non-Offshorability

1. Face-to-Face
    - 4.C.1.a.2.l Face-to-Face Discussions
    - 4.A.4.a.4 Establishing and Maintaining Interpersonal Relationships (JK,B)

- 4.A.4.a.5 Assisting and Caring for Others (JK,B)
- 4.A.4.a.8 Performing for or Working Directly with the Public (JK,B)
- 4.A.4.b.5 Coaching and Developing Others (B)

2. On-Site Job

- 4.A.1.b.2 Inspecting Equipment, Structures, or Material (JK)
- 4.A.3.a.2 Handling and Moving Objects
- 4.A.3.a.3 Controlling Machines and Processes
- 4.A.3.a.4 Operating Vehicles, Mechanized Devices, or Equipment
- 4.A.3.b.4 Repairing and Maintaining Mechanical Equipment (*0.5)
- 4.A.3.b.5 Repairing and Maintaining Electronic Equipment (*0.5)

3. Decision-Making

- 4.A.2.b.1 Making Decisions and Solving Problems (JK)
- 4.A.2.b.2 Thinking Creatively (JK)
- 4.A.2.b.4 Developing Objectives and Strategies
- 4.C.1.c.2 Responsibility for Outcomes and Results
- 4.C.3.a.2.b Frequency of Decision Making

Note that these task measures are not completely independent: correlations are illustrated in Figure B.2. A independent components analysis of the entire O*NET database was able to explain over 95% of the dataset's variation with just 6 factors. Nonetheless, these factors seem to give appropriate results for the groups of occupations they describe (see Table B.1).

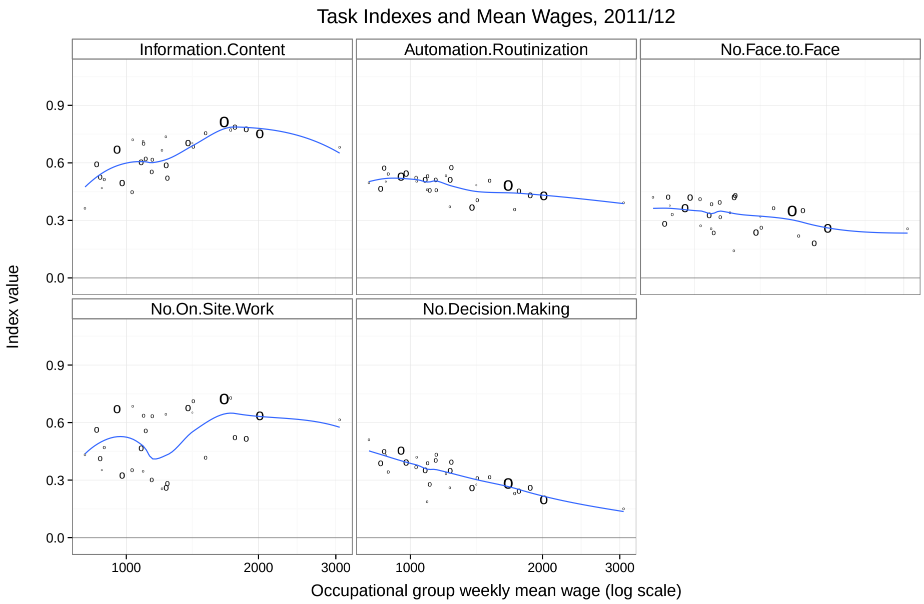

*Figure B.1: Mean occupational wage and task measure index values, using second combined grouping. Note the similarity of the observed trend to Figure 4.5, in which occupations have not been grouped. Census respondents reporting full-time work are shown. The loess regression line is weighted by population; circle areas are proportional to population for each occupation. Sources: ABS cat 2072.0, O*NET, US Dept of Labor.*

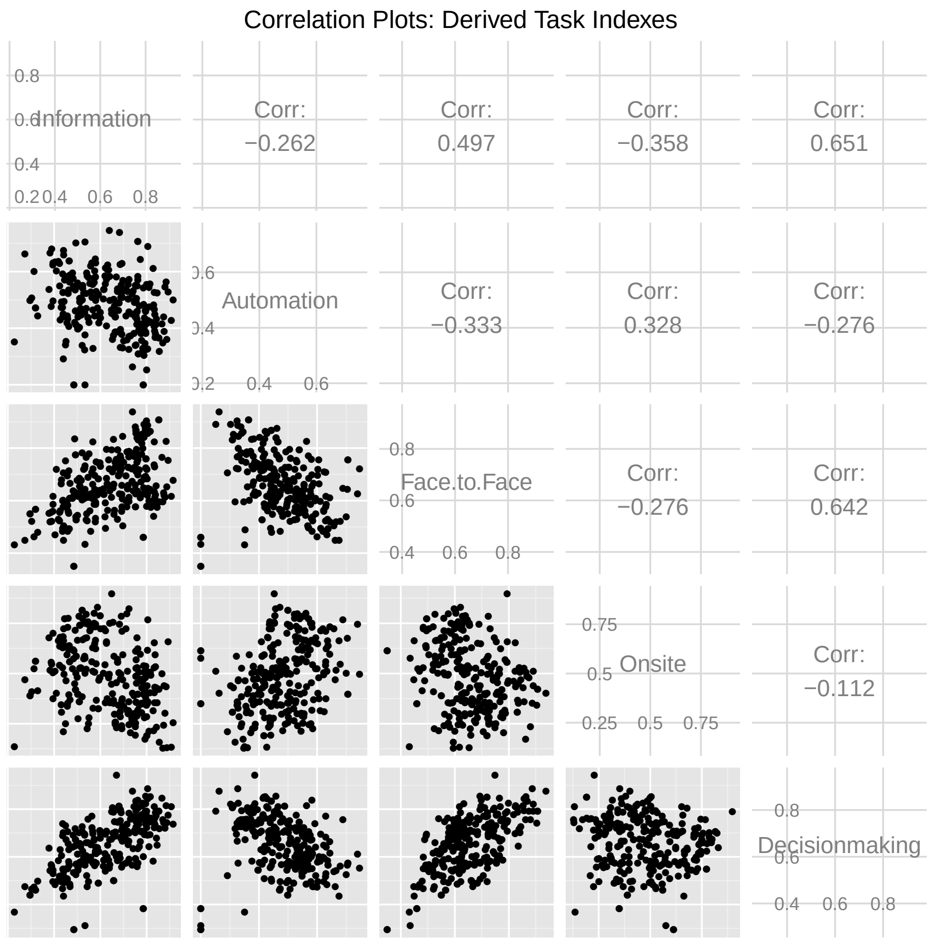

Figure B.2: Correlation plots: occupational task indexes for jobs at the ANZSIC occupational group level. Notice that the job indexes are not perfectly mutually independent. As might be expected, 'information content' is positively correlated with 'face-to-face' roles ($\rho = 0.497$*) and decision-making (*$\rho = 0.651$*), but negatively correlated with the job requiring on-site presence (*$\rho = -0.358$*). 'Routinization' is negatively correlated with both face-to-face contact (*$\rho = -0.33$*) and decision-making (*$\rho = -0.276$*).*

	Technology		Offshorability		
ANZSCO Major Occupation Group	Information	Automation	No Face-to-Face	No On-Site	No Decisions
1. Managers	0.427	-0.465	-0.919	0.401	-1.223
2. Professionals	0.913	-0.545	-0.475	0.577	-0.712
3. Technicians And Trades Workers	-0.424	0.258	0.598	-0.864	0.215
4. Community And Personal Service Workers	-0.511	-0.298	-0.565	0.291	0.453
5. Clerical And Administrative Workers	0.447	0.541	0.249	0.883	0.788
6. Sales Workers	-0.140	-0.087	-0.167	0.710	0.451
7. Machinery Operators And Drivers	-0.791	0.937	0.930	-1.096	0.868
8. Labourers	-0.955	0.730	0.811	-0.951	0.674
Std. Dev.	0.663	0.565	0.690	0.821	0.756
Mean	-0.129	0.134	0.058	-0.006	0.189

*Table B.1: Summary of task indexes, at the major group level, computed for occupation populations 2011 census. Sources: ABS cat 2072.0, O*NET, US Dept of Labor.*