Technological Change & Wages in Australia

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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 seek to 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 then test for trends in different types of occupations, an approach that has been used with success in foreign labor markets.

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.

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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. The period bore witness to a dramatic change in the distribution of incomes: Australia, like many developed countries, became less equal. After falling for the four decades following the Second World War, from the 1980s the gap between high and low income earners grew sharply, a period 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 labour, dividends from financial investments, government entitlements, other lump-sum cash transfers, capital gains on assets, and so on. The scope of these study is limited to just one of these flows: wages from labour 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 occuppational choice. Since young people must choose an educational path to equip them for a career, however there is some degree of uncertainty about the present value of a given career choice (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, wihtout 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.

By focussing on individuals' wages, as the flow of labour 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.

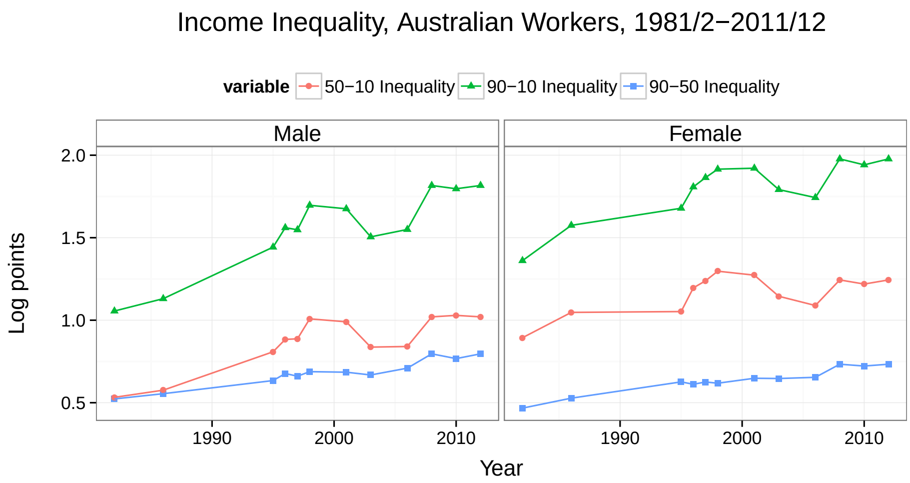

Figure 1.1: Change in income inequality measures for Australian workers, 1981/82 to 2011/12. The three measures refer to the differences between deciles of the log wage distribution. Unlike subsequent chapters of this study, which considers only full-time workers, these calculations include part-time 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 **??** 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 signficantly negative union effect on inequality Card, Lemieux, and Riddell (2004), Firpo, Fortin, and Lemieux

(2009).

The second major cause for Great Divergence is falling income taxation rates. The top marginal income tax rate in the 1908s 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, p31). 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 disproportionately complements 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 labour (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 indvidual's above-average level of productivity) is considerably higher. It is thus possible that unions 'amplify' inequality caused by skill-baised 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 U.K.), 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-skill managerial and professional jobs in the United States and Europe (Katz & Murphy, 1992). Since the canonical model includes *factor-augmenting* capital, it predicts monotone 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-skill 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-skill jobs, 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 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 (non-)Granger 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.

This research is structured according to three related, but separate lines of inquiry. In Chapter 2, we review the emprical evidence for skill-biased technical change, and produce estimates of the skill premium for recently-relased data. In Chapter 3, we extend our analysis to consider whether the impact of SBTC is polarizing, rather than simply widening, the income distribution. And finally, in Chapter 4 we seek to quantify the channels by which changes in the income distribution have occured, by decomposing changes in the income distribution into the tasks that comprise occupations. Finally, in Chapter 5, we review and suggest avenues for further research.

Chapter 2

Theoretical Literature

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, Gonner, and Li (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 technological change and income. Studies such as Mankiw, Romer, and Weil (1992) demonstrated that, if the Solow model is augmented to include a measure of human capital as a factor of production, then the model explains cross-country variation in the level of income very well indeed. However, as elegant and convenient as the neoclassical growth model is, and its success at explaining the dispersion of incomes between countries notwithstanding, 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. For that, more sophisticated models were needed.

2.2 Rising U.S. 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 on onto this trend, and a more nuanced understanding of technology on 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 U.S. men could be explained by the decline in the unionization rate. If it is accepted that 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 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). An equally plausible explanation for the observed trends that is independent of any qualitative change in the nature of technology or jobs; instead, 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 U.S. 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. study the relationship between wage rates for white males between 1963 and 1979, and macroeconomic measures of output and wages both in the U.S. 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 labor by enabling the substitution of capital for labor. Using logitudinal data gathered from census files, S. J. Davis and Haltiwanger (1991) argue that, though 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 expands, and the demand for manual labor softens. Krueger (1993) expands on this argument, and using microdata on individual workers, finds a premium associated with those occupations that involve computer use.[1]

2.3 Models of Skill-Biased Technological 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 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 different 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

[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.

Smith (1776, p. I.3). Tinbergen recognized that it would be unwieldy to attempt to model every 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 labour 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 initiate a 'race' for investment in education, as unskilled workers seek to enter education 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. In the jargon, 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 benefit 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.

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 deployed by a large number of authors analyzing skill-biased technology (Katz & Murphy, 1992; Goldin & L. F. Katz, 2007, e.g.). Before discussing the empirical evidence for SBTC, we will briefly outline the main features and implications of this model, following the notation employed by Acemoglu and Autor (2011)

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 CES aggregate production function, with elasticity of substitution σ, where $\sigma > 1$:

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

For our purposes, we are interested in two claims about relative wages made by this model: first, that technological change or a generalized shift from low-skilled to high-skilled work should never cause low-skilled wages to decrease, and second, that technological change should result in a monotonic increase in wage 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 (C.1) with respect to labor supply:

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

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

The first claim follows from differentiating these wage equations. First, 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, notice 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.

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

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

2.5 Alternative Perspectives on SBTC

A crucial assumption of the SBTC model is that, like the Solow (1957) growth accounting scheme, all technological changes are 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 automated tellers and a wide range of electronic service delivery which 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:

$$\text{capital, labour} \xrightarrow{F} \text{output.}$$

The *task approach*, presents an alternative perspective. Rather than viewing output as a direct function of resource inputs, it separates the tasks performed by labor and technology, allowing substitutions between factors (Autor, 2013; Acemoglu & Autor, 2011):

$$\text{capital, labour} \longrightarrow \text{tasks} \xrightarrow{F} \text{output}.$$

By separating the factors that produce tasks, and the tasks required for production, this approach facilitates the inclusion of worker *skills* in 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 driving force behind the industrial revolution Goldin and 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 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 driving force behind 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 for this trend, both because many middle-skilled jobs can be substituted by computer capital, and because communications technologies enable firms to out source 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 'non-routine.' 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 non-routine 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. Non-routine tasks can only be performed by non-rountine 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:

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

Since routine labour 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 non-routine tasks are imperfect substitutes in production, a decrease in the cost of routine task inputs also causes an increase in the demand for non-rountine tasks. So, if the supply of non-routine labour 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 is not general enough to 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 intuition behind this analysis stems 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. The model is sophisticated enough to handle any number of occupations, and distributions of individual skill. For our purposes, let us consider Roy's original simple thought experiment, a remote village where individuals with heterogeneous skills must choose between just two occupations: hunting rabbits and fly fishing.

The level of skill required to practise these jobs is quite different: hunting rabbits, which are described as 'slow and stupid,' is easy. As a result, the returns 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 labour 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 to any 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 models can be generalized to any number 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 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

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

for fishing, and

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

for rabbit hunting, where σ^2 is the variance of individuals' skill ratios, $\log(F_i/R_i)$, 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 in previous chapters 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 labour. 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 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 affords 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 and 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, 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 skill workers will perform tasks where $i \in (I_H, 1]$, medium-skill workers will perform tasks where $i \in [I_L, I_H]$ and low-skill 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 a 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 labour, 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.

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-parameteric and semi-parametric evidence for wage-setting models are drawn from wage distribution.

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, since one of the key explanations for SBTC includes globalization and the worldwide proliferation of new technology, the evidence for SBTC in Australia is does not exactly match the US and European experience. However, many studies have confirmed a growing demand for skilled labor, as well as an associated growth in its supply.

3.1 Occupational Changes in the 1980s

Beginning in the 1980s, a divergence between the rental rates of skilled an 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, if other factors are held constant 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 identify 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 be explain this jump in educational attainment: in the 1970s, students who continued college study were exempt from service in Vietname, and returning veterans were granted scholarships via the G.I. bill Acemoglu and Autor (2011). Nonetheless, the two labor market trends emerging from this literature were a continual 'up-skilling' of the workforce

[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.

since the 1980s, and a steady increase in the 'college premium', the average premium paid to workers who had attained college degrees or higher.

3.1.1 Upskilling in Australia

Occupational classification schemes such as the ASCO (Castles, 1986), and the ANZSCO (Trewin & Pink, 2006) include a numeric skill ranking for each occupation. Although the use of these statistics has been somewhat controversial[2], they do provide simple categories by which descriptive analysis of the skill distribution can be performed.

Cully (1999) divides employment data into five skill levels, and analyzes changes in the number of jobs at each category between 1986 and 1997. 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 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 conclusion is reached by Wooden, 2000, who expands Cully's methodology to also consider growth in terms of hours worked.

The college premium is linked to the supply of labor by Card and Lemieux, 2001. They note that the rising college premium measured in the data is attributable almost entirely to younger cohorts of workers, and especially for men in their early thirties. They argue that the driving force behind the rising college premium is a slowdown in the pace of educational attainment, relative to the demand for labor.

Australian labor market definitely increasing in (1) skills, (2) knowledge intensity. Esposto (2012) Esposto and Abbott (2011) Borland, 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

3.1.2 Direct Measures of Technical Change and Skill Premia

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 economic model—so the results are less susceptible to specification biases. To support the claim of SBTC, there are two claims that we want to see verified from sample surveys: first, that technology adoption is growing, and that the nature of work changes as a result (existence of technical change). Second, we expect to see that this technology impacts primarily on those with high skills (existence of skill bias).

Qualitiative research on the nature of computerization strongly supports the claim that technology dramatically 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 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 process 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 machiens. 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) employs 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 controls, 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, individuals' unobserved ability is likely to be correlated with computer use. Despite the inclusion of proxies for 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 Rising College Premia

Recall from Section **??** that, as the high-skilled technology 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 skill 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,

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

which when substituted into (2.6) yields a regression model of the following form:

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

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 following decade reasonably well, although it does under-predict the true level of between-group inequality somewhat from 2002 onwards.

3.2.1 College Premia in Australia

Somewhat surprisingly, college premia are 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 unmployment), 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 their respective demands, creating no scarcity premium in the labor market.

No college premium was found by Coelli and Wilkins (2009), who follows a similar procedure to Katz and Murphy (1992). He employs 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 finds that, that although a university premium exists, it is not rising, as it is in the United States and Europe.

Coelli suggests two novel interpretations for this finding. First, he notes 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. He also points 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.

3.2.2 Rising Skilled Labor Share

Both the 'canonical' model and the Ricardian models of occupational choice discussed in Chapter 2 make predictions about the proportion of skilled and unskilled labor employed, in the presence of SBTC.

Under the canonial 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, at the industry level. 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 CES production function and a flexible (translog) model to estimate changes in the shares of high-skill 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 more highly skilled work force.

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. As well as other globalization indexes, they find that technology investment, interpreted as a proxy for SBTC, Granger (non-)causes increases in inequality, measured as the Gini coefficient.

3.2.3 Test of Changing Wage Shares

Using measures of the tasks involved in various occupations derived from the Dictionary of Occupational Titles, a manual compiled by the US Department of Labor describing the skill and activity content of occupations, as well as industry-level measures of wages and employment by occupation, Autor et al. (2003) show that this model explains a considerable proportion of the dispersion of wages in the United States between 1960 and 1998, computerization led to a substitution in the observed levels of employment, away from routine tasks and toward cognitive tasks. Likewise, Goos and Manning (2007) show a similar trend in the United Kingdom: between 1975 and 2003, they find a increase in the number of "lovely" (high-skill, high-wage) jobs and "lousy" (low-wage, low-skill) 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).

3.3 Decomposition Methods

Empirically, we take as our point of departure the analysis of the US occupational wage structure performed by Fortin, Lemieux, and Firpo (2011), who build on the work of Oaxaca (1973) and Juhn et al. (1993) to decompose the impact of demographic variables and occupational tasks on the wage structure. Following Autor and Acemoglu (2012) and Fortin et al. (2011), we assume that workers self-select into occupations based on comparative advantage, in a model reminiscent of Roy's (1951) model of occupational choice.

In the previous two chapters, we assumed little about the functional relationship between specific skills and wages. Decomposition methods are especially powerful because they are able to extract relatively rich information from the data. This strength comes at the price of relatively strong assumptions imposed on the data in order to guarantee parameter identification; the limitations these assumptions bring are shared by all decomposition methods. These assumptions are discussed in detail in section 3.3.2, and mostly stem from the fact that decompositions provide only 'shallow' analyses of economic phenomena, and are not able to model 'deep,' structural properties of the labour 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 labour market depends only on the supply and demand for skills in that occupation.[3] This assumption is questionable: it is quite likely, for example, that a collapse in the demand for labour in one occupation, would cause some workers to change their occupational affiliations, triggering a shift in the supply of labour 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.

The next step in the analysis is to decompose changes in the log wage distribution according, according to task index measures. The decomposition methods upon which this study is based were first considered 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

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

mean wages paid to men and women. Let the difference in the mean wage for men and women be Δ:

$$\Delta = E[\ln y_m] - E[\ln y_f]. \tag{3.1}$$

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 the fact of 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 (3.1), the difference of expected log wages can be decomposed as,

$$\begin{aligned} \Delta_O &= E[X_m]'\boldsymbol{\beta}_m - E[X_f]'\boldsymbol{\beta}_f \\ &= \underbrace{E[X_m]'(\boldsymbol{\beta}_m - \boldsymbol{\beta}_f)}_{\Delta_S} + \underbrace{(E[X_m]' - E[X_f]')\boldsymbol{\beta}_f}_{\Delta_X}. \end{aligned} \tag{3.2}$$

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 (3.2) 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 study at hand, 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, corresponding to periods when the Survey of Income and Housing was conducted: 1981-2 and 2009-10. For simplicity, we refer to these time periods as $T = 0$ and $T = 1$, respectively. Instead of sex, in our case the explanatory variables of interest is a given by vector of task content indexes for each occupation.

Unlike Oaxaca, we must make one additional (and somewhat heroic) assumption, which we call *job uniformity.* In Oaxaca's study, he was able to take for granted that the meaning of the explanatory variables was invariant for both groups. for which the difference between maleness and femaleness can be assumed to be unfiorm over the entire period. The procedure for constructing these indexes is described in the data appendix, Section B.1.1.

3.3.1 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. Ideally, we would like to compute a decomposition similar to (3.2), but which decomposes changes in the αth 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 compute an 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:

$$\begin{aligned} \Delta^\tau_O &= q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=0}) \\ &= \underbrace{q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=1})}_{\Delta^\alpha_S} + \underbrace{q_\tau(F_{Y_0|T=1}) - q_\tau(F_{Y_0|T=0})}_{\Delta^\alpha_X} \end{aligned} \tag{3.3}$$

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, as described in (3.3), can be performed using an OLS regression on the recentered influence function of the distributional statistic in question. 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,

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

Then the estimated coefficient $\gamma_t^{q_\tau}$ of an OLS regression of $RIF(y_t;q_\tau)$ on 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 (3.3) in a similar form as (3.2),

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

Under the ‘ignorability’ assumption, discussed below, both of these components of the decomposition are identified.

3.3.2 Data Requirements for RIF-Regression

One condition required for RIF-regression is 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 1 (Overlapping support)**.** *Let the support of wage setting fac-*

tors 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 1 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 1981-2. Despite to the small sample size, the data are only available at a two-digit level of aggregation, so that none of the occupations listed in the ANZSIC were missing a counterpart from 1981-2. A correspondence was easily found between two-digit ANZSIC groups and 1981-2 occupations, which were available at the three-digit level.

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 2 (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 assumptions stated so far are both plausible, and sufficient for identifying the wage structure component ($\hat{\Delta}_S$) and endowment effect component ($\hat{\Delta}_X$) of the aggregate decomposition. While this aggregate decomposition is useful, even more useful would be the ability to separate out the components of Δ_X or Δ_S into the contributions of each independent variable, the so-called 'detailed decomposition'.

(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 following independence condition, found in Matzkin (2003), must hold:

Assumption 3 (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 (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, that the independence property is violated.

However, the impracticality of Assumption 3 is avoided by the linear functional form imposed by Assumption 4 (Fortin et al., 2011, p.28). Furthermore, the linear functional form assumption allows for heteroskedasticity. This this application, this is a useful property, since income variance increases with educational attainment.

3.3.3 Re-weighting the counterfactual distribution

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, in this application, 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 labour 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 labour 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.

In order to create a comparable counterfactual wage distribution, Firpo et al. (2011) suggest a hybrid approach, where the data in period 0 are reweighted so that 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 $F_{Y_0}^C$ that exhibits the characteristics of period 0, but with the wage structure of period 1:

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

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

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

Fortin et al. (2011) 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.

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 (3.3) 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 composition effect:

$$\begin{aligned}\hat{\Delta}^{q_\tau} &= (\hat{\Delta}_{S,p}^{q_\tau} + \hat{\Delta}_{S,e}^{q_\tau}) + (\hat{\Delta}_{X,p}^{q_\tau} + \hat{\Delta}_{X,e}^{q_\tau}) \\ &= \underbrace{\left([\bar{X}_{01} - \bar{X}_0]\hat{\gamma}_{01}^{q_\tau} + \bar{X}_{01}[\hat{\gamma}_{01}^{q_\tau} - \hat{\gamma}_0^{q_\tau}]\right)}_{\hat{\Delta}_S^{q_\tau}} + \underbrace{\left(\bar{X}_1[\hat{\gamma}_1^{q_\tau} - \hat{\gamma}_{01}^{q_\tau}] + [\bar{X}_1 - \bar{X}_{01}]\hat{\gamma}_{01}^{q_\tau}\right)}_{\hat{\Delta}_X^{q_\tau}}.\end{aligned} \tag{3.4}$$

This decomposition can be performed on income surveys of repeated cross-sections of the same markets over time.

Chapter 4

Empirical Work

4.1 Data

To test the theory of changes in the occupational wage profiles outlined above, we require survey 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 O*NET database, published by the US Department of Labor. Details of both the task measures and SIH are discussed in detail in Sections A.0.4 and B.1.1 of the data appendix. We shall therefore only briefly review the salient features of the data sources as they relate to this analysis. For further details, refer to Appendix A.

4.1.1 Survey of Income and Housing

To bring the SBTC model to the data, we employ the Survey of Income and Housing, a hierarchical clustered household survey conducted by the ABS every 2-3 years since 1995, and also for the fiscal years 1985-6 and 1981-

2. The survey provides detailed information about respondents' labor and non-labor income sources, as well as data on age, educational attainment, hours worked and industry and occupation. For the surveys conducted between 2000 and 2010, as well as the 1981-2 survey, the data include detailed occupational data, 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).

To facilitate inter-temporal comparisons, we must eliminate effects which arise as a result of mechanical, demographic shifts. Between 1982 and 2010, the number of women in the work force has increased dramatically, and the same period has seen an evolution of the educational and age composition of the work force, and the rate of casual and part-time employment has increased. Following Acemoglu and Autor (2011), we therefore include only full-time workers for whom labor forms the primary source of income. We further composition-adjust each survey to match 2010 demographics by linearly scaling the survey selection weights for each age group/sex/educational group cell. All computations in this study treat these adjusted weights as inverse selection probabilities.

Repeated cross-sectional measures of the income distribution for full-time salaried workers in Australia are computed using data from the SIH. Consistent with previous work, we consider only the subset of respondents who report working full-time, and whose primary source of income are either employer wages and salaries, or who receive income from an unincorporated business. In order to compare the 'market value' of skills, we record employee take-home wages (or revenue from an unincorporated business, after tax), including any additional payments such as entitlements, tips, and bonuses. Revenue from government payments, investments, and so on are ignored.

Real incomes are nominal incomes deflated by the average CPI for the four quarters of the fiscal year spanning the survey.

Changes in the occupational coding schemes pose a challenge. In each of the three surveys considered, the occupational coding schemes are different, and cannot be compared directly. 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. (A more detailed discussion of the coding systems employed can be found in Appendix Section A.0.4).

For the purposes of this analysis, the income distribution within occupations (or groups of occupations) of different time periods must be comparable. But in the absence of a classification scheme that permits comparison between periods, it is not possible to analyze changes in subsets of the wage distribution. 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, hybrid classification schemes that merged occupations into comparable groups were developed, and are described in detail in the Appendix. There are two such schemes: COMBINEDI, comprising 29 hybrid occupations, for comparing the 1981/82 survey with 2011/12, and COMBINEDII, with 28 hybrid occupations, for 2000/01 and 2011/12 (see Tables A.1 and 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.

4.1.2 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, although detailed occupational classifications are available for Australian data, these taxonomies do not make available quantitative measures of job attributes.[1] The lack of quantitative data for Australian jobs need not be a limitation, however. Goos, Manning, and Salomons (2009) map occupations for Europe and the U.K. to the U.S. occupational classification scheme in order to exploit O*NET, a comprehensive database of occupational activities, knowledge, job attributes, and working conditions produced by the U.S. Department of Labor. For this analysis, we construct a similar mapping, between the ANZSCO and O*NET at the unit group (four digit) level. We only briefly discuss the procedure for deriving task measures here; a detailed discussion can be found in appendix Section B.1.1.

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 simply its massive 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

[1] Some job 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 Section B for a discussion.

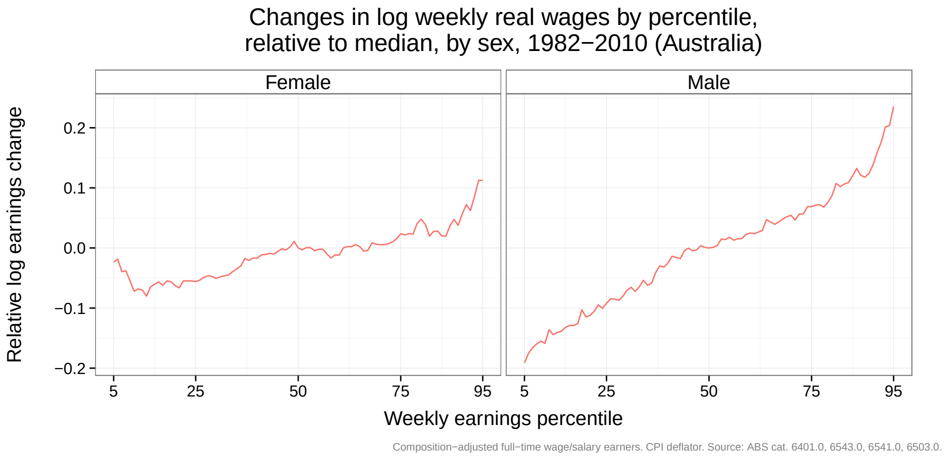

Figure 4.1: Change in weekly wage by percentile, 1981-2010, Males and Females. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotone for males in lower percentiles. Source: Survey of Income and Housing.

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*.[2]

4.2 The Canonical Model

4.2.1 Results

If SBTC explained the widening of the income distribution, we would expect to observe the premium accruing to 'skilled' labor increasing with time. Figure 4.1 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 skill, then it is apparent that, over this period, wages more grew for high-skill individuals much faster than

[2]These scales are not completely independent. See Appendix Section B.1.1 for a discussion.

for low-skill individuals. It would therefore be expected that the premium accruing to higher educational attainment would show a similar trend.

In the United States, at least, 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) employs 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 4.2 shows the log skill premium for Australia and the United States between 1982 and 2008. Rather than any fundamental differences in the nature of the demand for skills, Coelli and Wilkins (2009) attributes this difference in Australian workers to differences in the nature of Australian educational qualifications. In Australia, University degrees are available to a wider range of candidates and for a wider range of disciplines than those who would traditionally have undertaken university studies in the United States. As a result, tertiary educational attainment may be a poor proxy for 'skilled' work in Australia.

The SBTC model also claims that, even if technology exhibits skill bias, wages for all skill groups should increase monotonically. Figure 4.3 plots the cumulative change over time for three wage percentiles, 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.

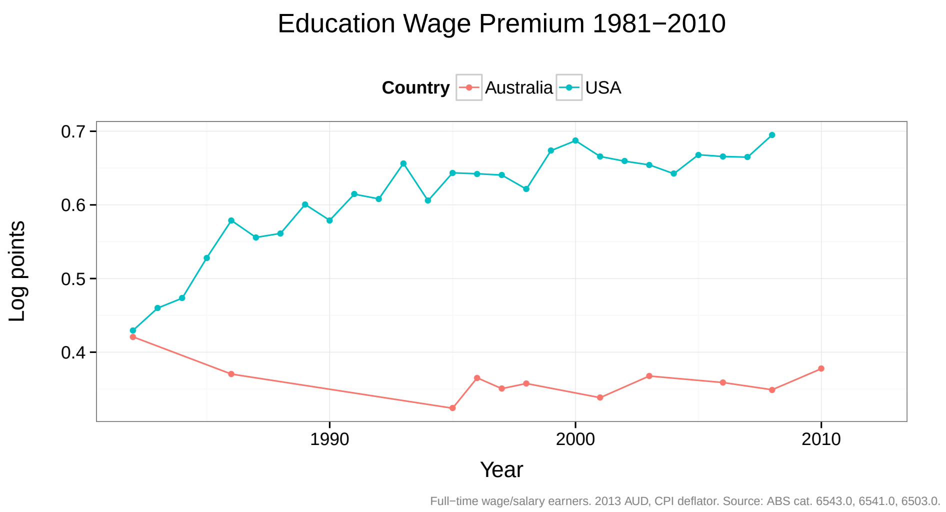

Figure 4.2: University/non-university log wage premium, Australia and the United States. The figures show the difference between the mean log weekly income for workers who have attained a bachelor degree or higher, and the mean weekly income of other workers. Only full-time workers whose main sources 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).

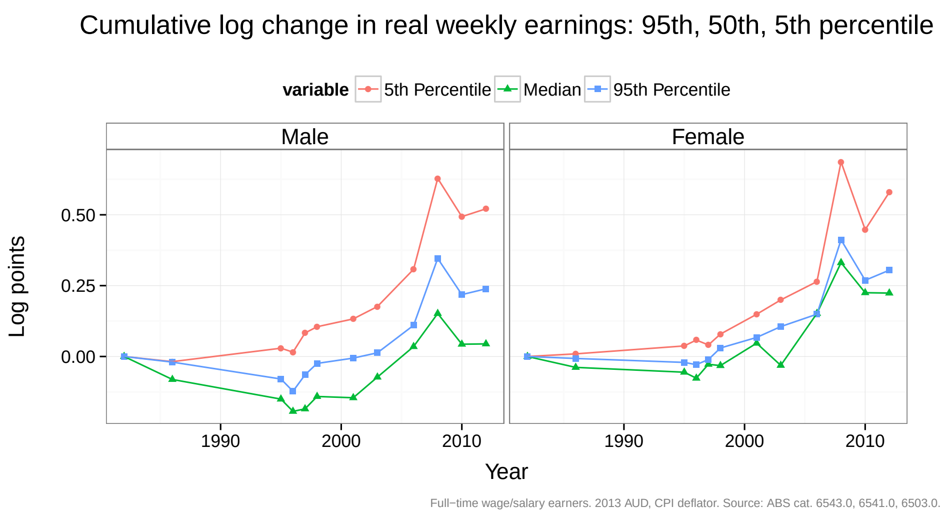

Figure 4.3: Cumulative log change in real weekly earnings, 5th, 50th and 95th percentiles, 1982-2010. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotone for males in lower percentiles. Source: Survey of Income and Housing.

4.2.2 Discussion

That the income distribution is widening, but the skill premium is *not* driving the change, suggests one of 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 given by Autor et al. (2003). Technological change may not be complementary to all types of labor; it may replace many types of labor entirely.

4.3 The 'Disappearing Middle'

4.3.1 Model

To test this pattern for Australian data, we can augment (C.1) 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:

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

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.[3] To test these pre-

[3]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

dictions, Michaels et al. (2013) specify a simple translog flexible 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.

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

As Michaels *et al.* point out, the polarization hypothesis is consistent with $\alpha_{MS} < 0$ and $\alpha_{HS} > 0$.

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 partition occupations according to the tasks they involve, according to the occupational classification coded in the SIH. For the purposes of this very simple and informal model, we divide occupations into three categories: 'non-routine manual' (low-skilled), 'routine' (middle-skilled), and 'non-routine cognitive' (high-skilled.) Capital series were derived from national accounting data. Our data include two different measures of ICT capital: *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

share, however, are unambiguous.

out variation in the data, the period 1996-2010 was divided into two seven-year periods.

4.3.2 Results

The results from estimating (4.1), 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, $\alpha_{MS} < 0$ 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 opposites in all estimates. This suggests that software capital may in fact be a complement to medium-skilled labor. 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 im-

Figure 4.4: Change in wage share against change in: (1) log ICT electrical and electronic equipment capital ratio, (2) change in log ICT software capital ratio, (3) change in log ICT computers and peripherals capital ratio, by industry, Australia, 1996-2010. Fitted line computed using LOESS regression and 95% confidence interval. See note for Table 4.1 for more details.

Table 4.1: Wage Share Change Estimation Results: 1996-2010

	Dependent variable:					
	$\Delta SHARE^H$		$\Delta SHARE^M$		$\Delta SHARE^L$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δlog *equipment*	0.037	0.081	−0.144	−0.249**	0.107	0.169*
	(0.100)	(0.080)	(0.108)	(0.094)	(0.099)	(0.084)
Δlog *software*	−0.018		0.109*		−0.091*	
	(0.052)		(0.056)		(0.052)	
Δlog *other capital*	0.118		−0.173		0.055	
	(0.176)		(0.191)		(0.176)	
Δlog *value added*	0.113	0.071	0.035	0.030	−0.148	−0.102
	(0.163)	(0.127)	(0.176)	(0.149)	(0.163)	(0.133)
Constant	0.040	0.055	−0.102	−0.095	0.062	0.040
	(0.073)	(0.060)	(0.079)	(0.070)	(0.073)	(0.063)
Observations	30	30	30	30	30	30
R^2	0.068	0.044	0.343	0.210	0.251	0.151
Adjusted R^2	−0.081	−0.026	0.238	0.152	0.132	0.089
Residual Std. Error	0.101 (df = 25)	0.098 (df = 27)	0.109 (df = 25)	0.115 (df = 27)	0.101 (df = 25)	0.103 (df = 27)
F Statistic	0.455 (df = 4; 25)	0.627 (df = 2; 27)	3.268** (df = 4; 25)	3.593** (df = 2; 27)	2.100 (df = 4; 25)	2.409 (df = 2; 27)
Note:						*p<0.1; **p<0.05; ***p<0.01

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. Source: ABS (Survey of Income and Housing and National Accounts).*

portant determinants of the evolution of the wage distribution.

4.3.3 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.

4.4 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 Australian labour 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 in Chapters 2 and 3 lend weight to Goos & Manning's (2007) more 'nuanced' interpretation of skill-biased technical change. 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 out-sourced by firms or automated by investments in labour-saving capital equipment. Under this hypothesis, specific attributes of these jobs allow them to be replaced or outsourced, shifts firms' demand curves for these types of labour to the left. As a result of an excess of supply over demand, wages in these occupations are bid down, and wages are both compressed and reduced.

The analysis presented in Chapter 3 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.

In this chapter, we present a more rigorous analysis, using data on occupational task content compiled by the U.S. Department of Labor to determine which occupations are likely candidates for automation and off-shoring. This data, made available as part of the O*NET database, provides measures of the types of tasks specific occupations entail. Adapting a procedure developed by JK as an extension to Autor et al. (2003), who adapt the US Dictionary of Occupational Titles, the predecessor to O*NET, to compile indexes for 'offshorability' and 'routinsation.' These indexes provide a quantiative foundation for comparing changes in the wage distribution and occupations at risk of structural change due to the processes of 'offshorability' and 'routinisation.'

Before analyzing changes over time, we first describe the relationship between task indexes and occupational conditional means in a single cross-section of the data. Figure 4.5 plots the relationship between mean full-time wages, as measured in the 2011 Census, and the task measures constructed from O*NET data.[4] The data are plotted at the ANZSCO unit group (four digit) level, with a loess regression line, weighted by occupation population, superimposed.

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 becoming stronger

[4]Census data are used in Figure 4.5, rather than the SIH, because occupational wages are available a greater level of detail: ANZSCO unit groups (four digit), rather than minor groups (two digit). The same chart is replicated using SIH data in Figure **??**; the patterns that emerge are almost identical.

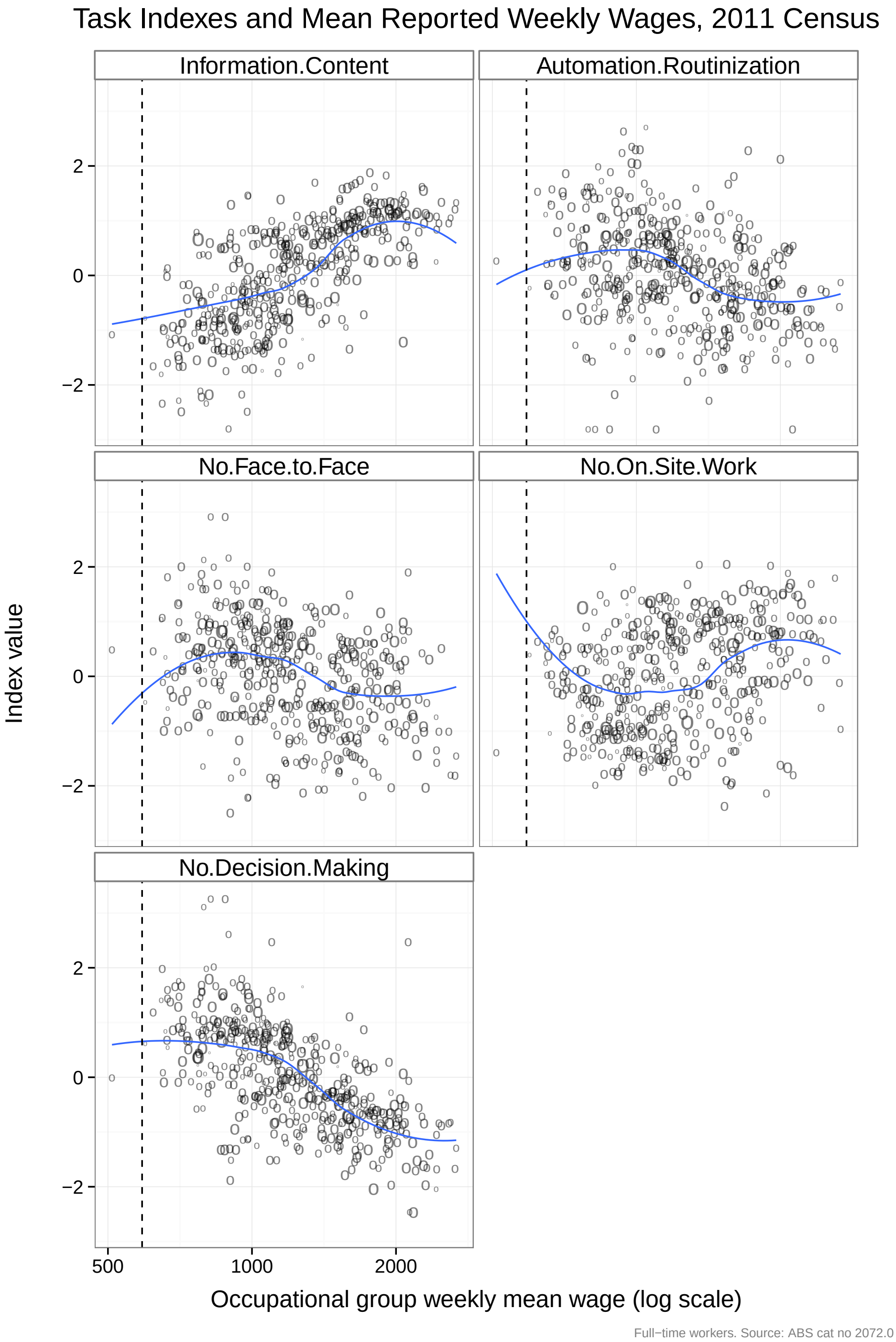

*Figure 4.5: Mean occupational weekly wage and task measure index values, at ANZSCO unit group (4-digit) level. The vertical dashed line is drawn at the level of the National Minimum Wage, of $589.30 per week. Census respondents reporting full-time work are shown. The loess regression line is weighted 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.*

over time.

4.5 Wage Profile Changes

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 4 (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, and $u_{ijt} \sim i.i.d$ captures idiosyncratic characteristics of each worker.

This is a strong assumption, which enjoys limited empirical support. Linear additivity implies that the labour 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 above, fly fishing skills of any level do not earn a return for workers engaged in rabbit hunting.

Firpo et al. (2011) perform two separate 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 was a good instrument 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 off-shore 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:

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

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

4.5.1 Results

The Roy model outlined above posits that, if the demand for labour of a particular typee 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 in Section 4.5 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 our task measures. 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), an 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 coefficient estimates between indexes; it is not clear that this would be at all meaningful.

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

The results in Table 4.2 stands 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 suggests a number of possible explanations. First, it is possible that the

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	−0.08		−0.12	0.11	
	(0.23)	(0.18)		(0.10)	(0.08)	
Automation/routinization	−0.39		−0.59***	0.20*		0.32***
	(0.26)		(0.19)	(0.11)		(0.08)
No face-to-face contact	−0.0002	0.11		0.02	−0.04	
	(0.23)	(0.18)		(0.10)	(0.08)	
No on-site work	0.09	0.45**		−0.07	−0.25***	
	(0.20)	(0.17)		(0.09)	(0.08)	
No decision-making	0.64**		0.45**	−0.33***		−0.28***
	(0.24)		(0.17)	(0.11)		(0.08)
Observations	28	28	28	28	28	28
R^2	0.49	0.33	0.29	0.57	0.38	0.40
Adjusted R^2	0.38	0.24	0.23	0.47	0.30	0.35
Residual Std. Error	394.16 (22)	434.36 (24)	437.70 (25)	173.56 (22)	199.75 (24)	192.35 (25)
F Statistic	4.27*** (5; 22)	3.90** (3; 24)	5.08** (2; 25)	5.80*** (5; 22)	4.84*** (3; 24)	8.27*** (2; 25)

Note: *p<0.1; **p<0.05; ***p<0.01
Occupational grouping 1 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	−1.01***		0.11	0.17***	
	(0.47)	(0.36)		(0.07)	(0.05)	
Automation/routinization	−0.49		−1.03***	0.07		0.15***
	(0.51)		(0.36)	(0.08)		(0.05)
No face-to-face contact	0.29	0.18		−0.03	−0.03	
	(0.48)	(0.32)		(0.07)	(0.05)	
No on-site work	1.11**	1.38***		−0.16**	−0.21***	
	(0.40)	(0.32)		(0.06)	(0.05)	
No decision-making	0.48		1.16***	−0.09		−0.19***
	(0.45)		(0.37)	(0.07)		(0.05)
Observations	29	29	29	29	29	29
R^2	0.48	0.44	0.29	0.51	0.47	0.34
Adjusted R^2	0.36	0.38	0.24	0.40	0.40	0.29
Residual Std. Error	15.43 (23)	15.23 (25)	16.85 (26)	2.27 (23)	2.27 (25)	2.48 (26)
F Statistic	4.18*** (5; 23)	6.67*** (3; 25)	5.40** (2; 26)	4.73*** (5; 23)	7.26*** (3; 25)	6.59*** (2; 26)

Note: *p<0.1; **p<0.05; ***p<0.01
Occupational grouping 2 used, with 29 occupational groups.

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 labour market.

One major difference with US labour market 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 level of the minimum wage suggests that the presence of non-linearities in the relationship between tasks and wages could be important.[5]

4.6 Tasks and Wages: A Decomposition Approach

4.6.1 Results

Figure 4.6 presents the results of unconditional quantile regressions of task measures against the occuptional wage profile, afer accounting for demographic and human capital variables.[6] On the left-hand side, the first classification scheme is illustrated, and on the right, the second. The top row shows the base period (1981/82 and 2000/01, respectively), and the bot-

[5]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.

[6]Eight dummies for potential experience, education, sex and martial status are included.

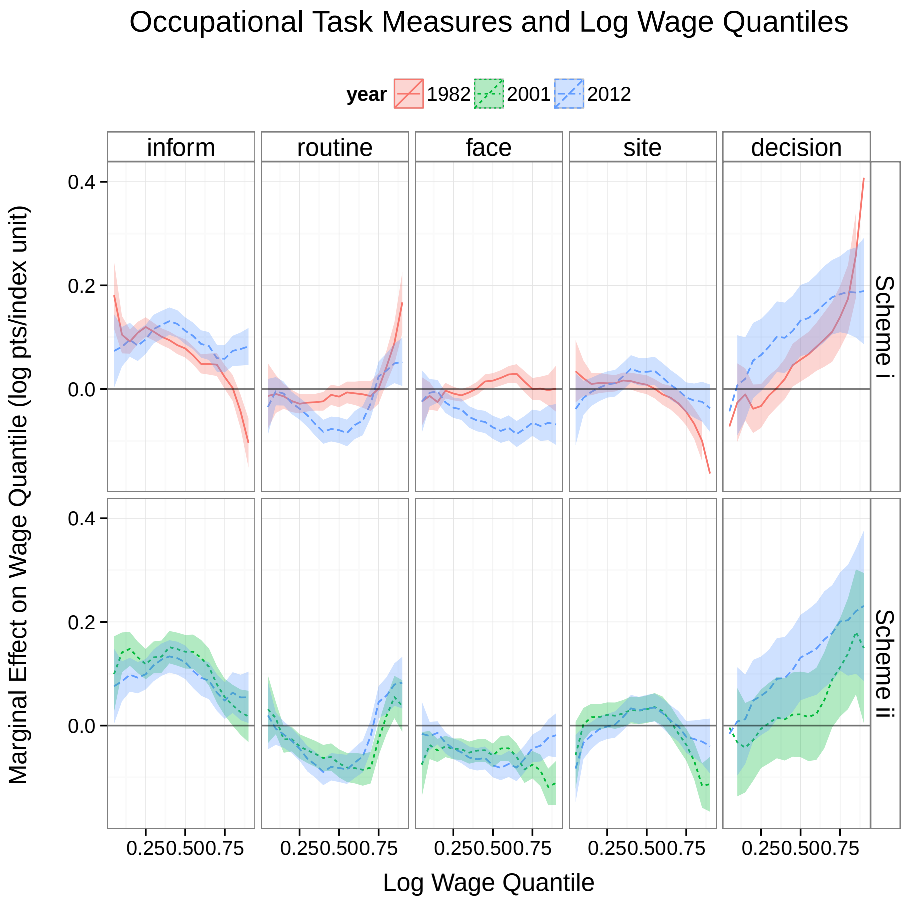

*Figure 4.6: Marginal log wage effect of task measures on log wage quantiles, 1981/82–2011/12 and 2000/01–20011/12, with shaded 95% confidence intervals. At any given quantile, overlap between the confidence band and the x-axis indicates a lack of statistical significance. The top row shows unconditional 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.*

tom row shows 2011/12 for both classification schemes. The horizontal axis shows the quantiles of the (real) wage distribution, and the vertical axis is measured in log points per scale unit. 95% confidence intervals are shaded, so that at each quantile, statistical signficiance is indicated by the shaded area not overlapping the horizontal axis.[7]

Figure 4.6 illustrates two important facts. First, notice that the marginal task impact curves differ between periods. Consequently, a unit change in occupational task measures is associated with a different impact on wage quantiles at the start and end of both periods. We will focus on these differences, below. Second, notice that marginal effects for each period and task measure appear to be related to quantiles (the x-axis) in a complex way. At this stage, we can conclude that the association between the wage distribution and task measures is highly nonlinear, and that the simple model estimated in (**??**) is not rich enough to capture the changes over time in the wage distribution.

Although their shapes are indicative, the difference between the marginal task effects between periods,

$$\partial \ln(w^q_{T=1})/\partial TC_i - \partial \ln(w^q_{T=0})/\partial TC_i,$$

need to be interpreted with care. Recall from the previous dicusssion that observed changes in the marginal income distribution can occur over time for two reasons. First, a change in the composition of the population of individuals self-selecting into occupations. If, for instance, individuals with a higher degree of human capital were to self-select into occupations with a higher level of a particular task measure, then the observed marginal effect

[7] Note that, since task measure scale units are essentially arbitrary, it is not meaningful to compare different task measures vertically.

of that task measure would increase. This change corresponds to the Δ_X term of (3.2). The second component of changes in the marginal effect of task measures is associated with structural changes in the occupational wage structure, denoted Δ_S. In the following section, we now formally de-compose the changes in the occupational wage structure into these two components.

4.6.2 Decomposition Results

4.6.3 Conclusions

Chapter 5

Conclusions & Further Work

References

ABS. (2013a). 5206.0 - Australian National Accounts: National Income, Expenditure and Product, Dec 2012. Canberra: Australian Bureau of Statistics. Retrieved from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5206.0Dec2012?OpenDocument

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."

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.

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.*

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. (2001, May). "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis." *The Quarterly Journal of Economics*, *116*(2), 705–746

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 Semiparametric 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.

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., & 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.

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., Gonner, E. C. K., & Li, Q. (1819). *The principles of political economy and taxation*. 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.0.4 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 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.

Survey 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.

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.

Educational Attainment

Sources of Income

As described in the data appendix, to ensure comparability for skills, only individuals who report a full-time wage as their primary source of income are included. (** NB: later we might attempt $ per hour)

A.0.5 Census

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.*

Appendix B

Task Measure Construction

One step which was skipped over in the informal analysis in the previous chapter 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 formalise 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.1.1 Occupational tasks: O*NET

The U.S. 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

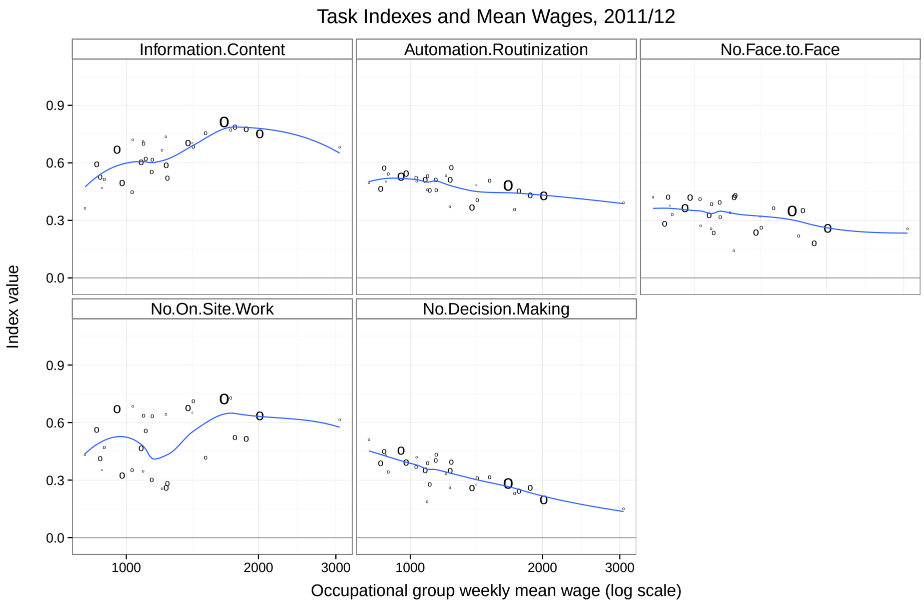

*Figure B.1: Mean occupational wage and task measure index values, using second combined grouping. Note the similarity of the observed trend to Figure 4.5, in which occupations have not been grouped. Census respondents reporting full-time work are shown. The loess regression line is weighted by population;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

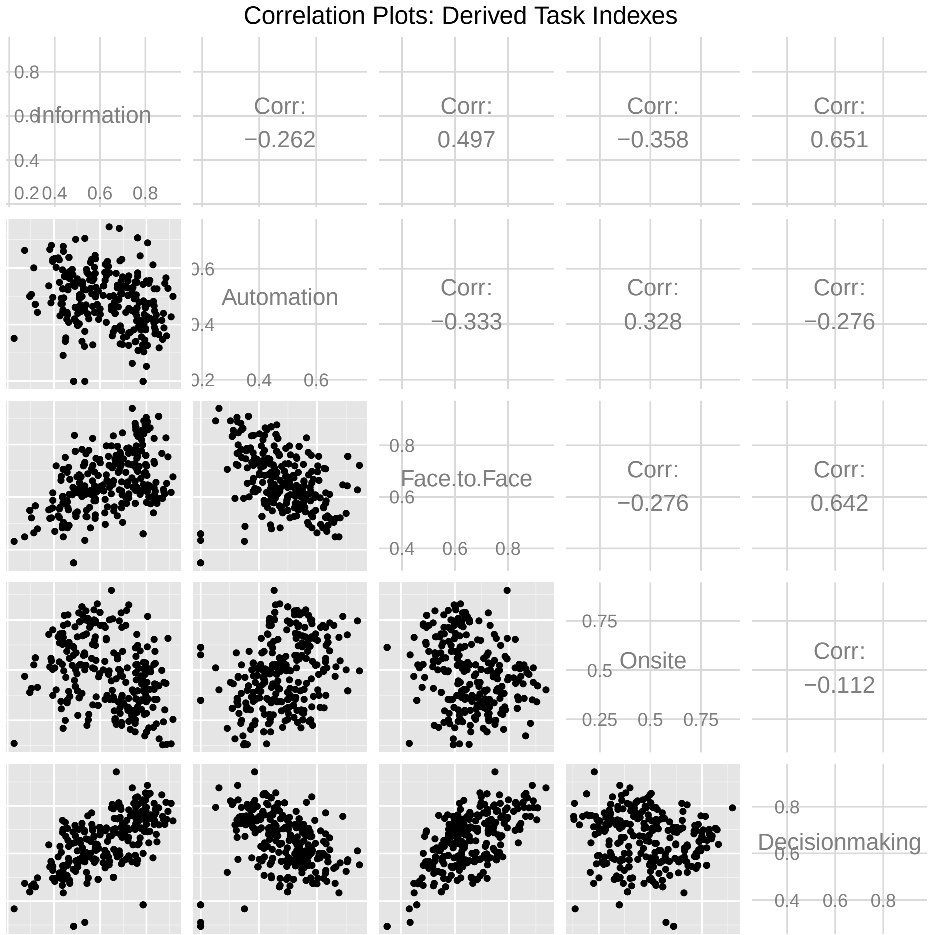

Figure B.2: Correlation plots: occupational task indexes for jobs at the ANZSIC 3-digit level. Notice that the job indexes are not perfectly mutually independent. As might be expected, 'information content' is positively correlated with 'face-to-face' roles ($\rho = 0.497$*) and decision-making (*$\rho = 0.651$*), 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 (*$\rho = -0.276$*).*

Appendix C

Proof of Propositions in Chapter 3

First, 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; but we do assume that the unit wage for each type of labor is fixed.

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:

$$H = \int_{i \in \mathcal{H}} h_i \, di \quad M = \int_{i \in \mathcal{M}} m_i \, di \quad L = \int_{i \in \mathcal{L}} \ell_i \, di$$

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

$$Y = \left(\gamma \left(C^{\eta} + H^{\eta}\right)^{\rho/\eta} + \beta(C + M)^{\rho} + \alpha L^{\rho}\right)^{1/\rho} \tag{C.1}$$

For convenience, we'll assume the share parameters are equal and sum to unity, i.e. $\alpha = \beta = \gamma = 1/3$.

Since the economy is competitive, the wage is given by each worker's marginal product, computed by taking the partial derivative of Y.

$$\begin{aligned}
w_L &= \partial_L Y \\
&= \alpha L^{\rho-1} \left(\gamma \left(C^{\eta} + H^{\eta}\right)^{\rho/\eta} + \beta(C + M)^{\rho} + \alpha L^{\rho}\right)^{\frac{1}{\rho}-1} \\
w_M &= \partial_M Y \\
&= \beta(C + M)^{\rho-1} \left(\gamma \left(C^{\eta} + H^{\eta}\right)^{\rho/\eta} + \beta(C + M)^{\rho} + \alpha L^{\rho}\right)^{\frac{1}{\rho}-1} \\
w_H &= \partial_H Y \\
&= \gamma H^{\eta-1} \left(C^{\eta} + H^{\eta}\right)^{\frac{\rho}{\eta}-1} \left(\gamma \left(C^{\eta} + H^{\eta}\right)^{\rho/\eta} + \beta(C + M)^{\rho} + \alpha L^{\rho}\right)^{\frac{1}{\rho}-1}
\end{aligned}$$

One way to achieve determinate comparative static predictions is to instead consider the *wage share*, computed as the wage bill for the labour type, divided by the total wage bill. These wage shares are:

$$\begin{aligned}
\theta_H &= \frac{Hw_H}{Hw_H + Lw_L + Mw_M} \\
&= \frac{\gamma(C+M)H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-1}}{\alpha(C+M)L^\rho + \beta M(C+M)^\rho} \\
\theta_M &= \frac{Mw_M}{Hw_H + Lw_L + Mw_M} \\
&= \frac{\beta M \left(C^\eta + H^\eta\right)(C+M)^{\rho-1}}{H^\eta\left(\gamma\left(C^\eta + H^\eta\right)^{\rho/\eta} + \alpha L^\rho\right) + \alpha C^\eta L^\rho} \\
\theta_L &= \frac{Lw_L}{Hw_H + Lw_L + Mw_M} \\
&= \frac{\alpha L^\rho}{\gamma H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-1} + \beta M(C+M)^{\rho-1}}
\end{aligned}$$

And the comparative statics are—

$$\begin{aligned}
\frac{\partial \theta_H}{\partial C} &= \frac{\gamma H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-2}\left(\beta M(C+M)^\rho \left(C^\eta(C(-\eta) + C + M(\rho-\eta)) - C(\rho-1)H^\eta\right) - \alpha C^\eta(C+\right.}{C\left(\alpha(C+M)L^\rho + \beta M(C+M)^\rho\right)^2} \\
&> 0 \\
\frac{\partial \theta_M}{\partial C} &= \frac{\beta M(C+M)^{\rho-2}\left(\alpha C(\rho-1)L^\rho\left(C^\eta + H^\eta\right)^2 + \gamma H^\eta\left(C^\eta + H^\eta\right)^{\rho/\eta}\left(C^\eta(C(\eta-1) + M(\eta-\rho)) +\right.\right.}{C\left(H^\eta\left(\gamma\left(C^\eta + H^\eta\right)^{\rho/\eta} + \alpha L^\rho\right) + \alpha C^\eta L^\rho\right)^2} \\
&< 0 \\
\frac{\partial \theta_L}{\partial C} &= -\frac{\alpha L^\rho\left(\beta M(\rho-1)(C+M)^{\rho-2} - \gamma C^{\eta-1}(\eta-\rho)H^\eta\left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-2}\right)}{\left(\gamma H^\eta\left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-1} + \beta M(C+M)^{\rho-1}\right)^2} \\
&\gtrless 0
\end{aligned}$$