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 also has the capacity to put others out of work entirely. Research from the United States and Europe suggests that technological change has indeed caused a 'polarization' of the income 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.

First, we link the wage share of middle-skilled occupations to investment in electronic and electrical capital goods. Next, we 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

This thesis seeks to explore the relationship between technological change and the recent secular increase in income inequality in Australia. We perform an empirical investigation of a number of models of technological change, beginning with the 'canonical' neoclassical model of skill-biased technology. We show that skill bias does not explain empirical regularities in the wage distribution. We show that, instead, models of the task content of workers' skills, of the type proposed by Autor, Levy, and Murnane (2003), go some way to explaining the changing remuneration patterns of the Australian workforce.

The second half of the 20th century has witnessed tremendous change for Australian workers. Since 1973, average real per capita incomes have approximately doubled (ABS, 2013a). Economic growth has added over three million jobs to the work force (ABS, 2013b). But the same period bore witness to a dramatic change in the distribution of incomes: in Australia, as well as in most developed countries, top percentile wage growth far outstripped that of lower-wage earners (Atkinson, 1997; Borland, 1999; Leigh, 2013). Although income inequality in Australia fell somewhat between the 1950's and 1970's, it has since risen consistently for the last 30 years, a period Leigh (2013) refers to as the 'Great Divergence'. (Leigh, 2005; Gaston & Rajaguru, 2009).

There are many causes of wealth inequality, and a great many reasons why the total lifetime wealth of a population may greatly diverge. In an indistrialized society such as

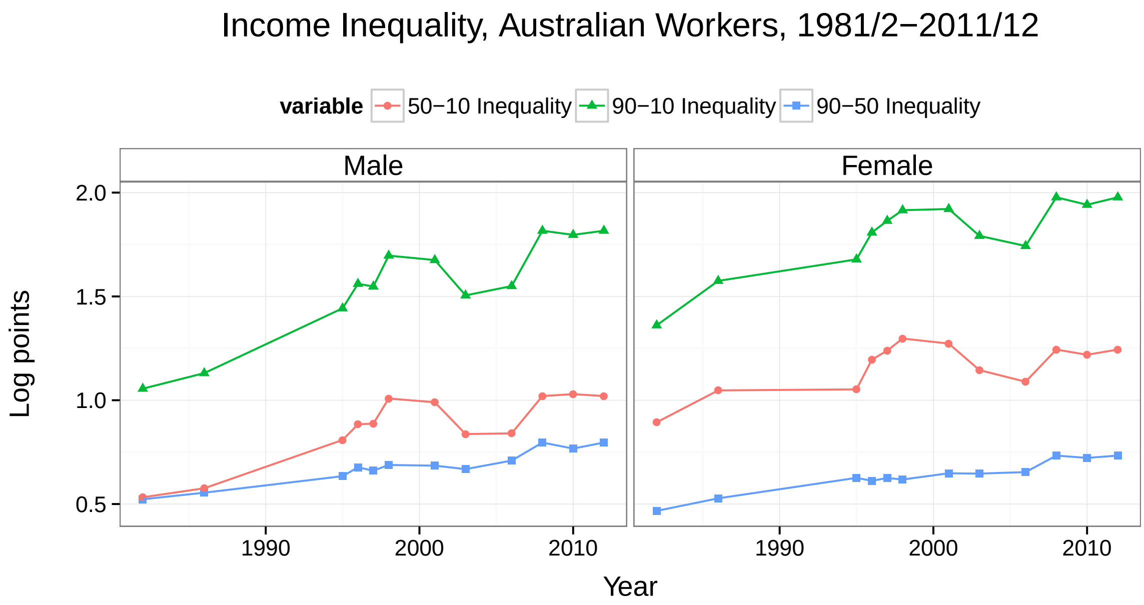

Figure 1.1: Change in income inequality measures for Australian workers, 1981/82 and 2011/12. Only workers with positive income are included, and calculations are weighted by the SIH survey weight. Source: ABS cat. 6543.0, 6541.0, 6503.0.

Australia, arguably one of the most important sources of inequality is income inequality, and in particular, wage inequality is of particular importance. Figure **??** illustrates three measures of wage inequality, over the period of the Great Divergence. During this period, 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.

Leigh (2013) cites three principal causes for this surge in income inequality: unions, taxes and technology. Unions tend to reduce income inequality, particularly 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 (()ACTU2013). 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 **Card2004**; 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).

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, 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. **Acemoglu2001** argue that increasingly 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 in the presence of skill-baised technical change.

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 a uniform 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, 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.[1]

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 *overpredicts* the magnitude of this differential for the United States (Autor et al., 2008). In Australia, a corresponding growth in the premium for tertiary qualifications has not been observed (Coelli & Wilkins, 2009).

There are, however, 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 et al., 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,

[1] ABS National Accounts, cat. no. 5204.0. 2012 dollars.

both in terms of remuneration and level.

1.1 The 'Task Approach'

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.

The *task approach*, a research program initiated by Autor, Levy, and Murnane (2003), presents an alternative perspective to the standard neoclassical production function. 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).

The task 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.

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.

1.2 ICT and Routinization

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.

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 Autor, Levy, and Murnane (2003).

Non-routine tasks, on the other hand, may improve, rather than replace, the efficiency of human workers. Indeed, as Borland, Hirschberg, and Lye (2004) found by studying the computer knowledge of a cross-section of Australian workers surveyed in 1992, computer knowledge accrues a skill premium of around 10%.

Thus computing capital is a complement to some kinds of task-performing labor, and a substitute for others. As Autor, Levy, and Murnane (2003) show, 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).

It is therefore plausible, that the widespread adoption of ICT is a major driving force behind compositional changes in the workforce.

1.3 Road map and Contribution

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.

In this thesis, we test the hypothesis that skill-biased technical change can explain the rise of inequality in Australia. In particular, we test whether the use of technology, in the form of ICT capital investment, automation and machinery, has displaced workers in certain kinds of jobs. And we attempt to decompose changes in the income distribution according to the type of tasks that workers perform in their jobs.

Chapter 2

Skill-biased technical change

A leading explanation for this divergence of incomes is that skilled work and new technologies are complements in production, or factor augmenting. This idea, developed by Tinbergen (1974), Katz and Murphy (1992) and others, suggests 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 et al., 2006).

We will take as a point of departure the standard model for analyzing skill-based technical change (SBTC). This model, dubbed the 'canonical' model by Acemoglu and Autor (2011) and 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 a uniform 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 et al., 2008).

2.1 Model

Consider a competitive economy with two different, imperfectly substitutable types of labor: high-skilled and low-skilled.[1] Workers are heterogeneous, with different levels of efficiency within each skill group. Let the total supply of high-skilled labor be H, and the total supply of low-skilled labor be L, and both types are paid the same wage, respectively w_h and w_ℓ. Production in this economy is governed by a CES aggregate production function, with elasticity of substitution σ, where $\sigma > 1$:

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_H H)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}}. \tag{2.1}$$

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 (B.1) with respect to labor supply:

$$w_h = \frac{\partial Y}{\partial H} = A_H^{\frac{\sigma-1}{\sigma}} \left(A_L^{\frac{\sigma-1}{\sigma}} (H/L)^{-\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \tag{2.2}$$

$$w_l = \frac{\partial Y}{\partial H} = A_L^{\frac{\sigma-1}{\sigma}} \left(A_L^{\frac{\sigma-1}{\sigma}} + A_H^{\frac{\sigma-1}{\sigma}} (H/L)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \tag{2.3}$$

The first claim follows from differentiating these wage equations. First, notice in (2.3) 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

[1] This section follows the notation employed by Acemoglu and Autor (2011).

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 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:

$$\log\omega = \frac{\sigma-1}{\sigma}\log\left(\frac{A_H}{A_L}\right) - \frac{1}{\sigma}\log\left(\frac{H}{L}\right). \tag{2.4}$$

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 (2.4) 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.

2.2 Data

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

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

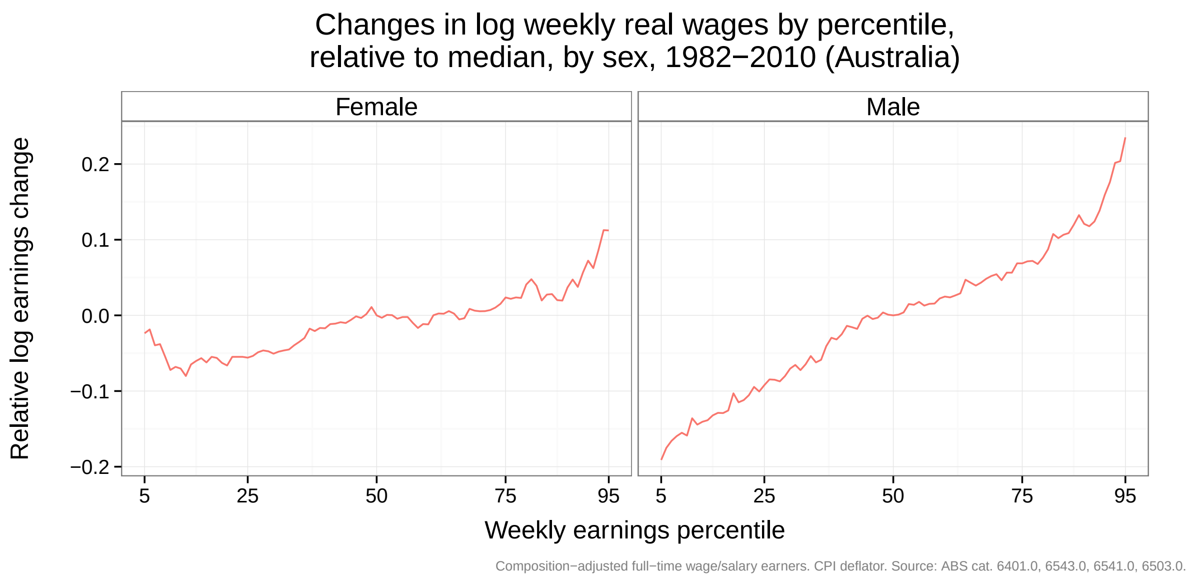

Figure 2.1: Change in weekly wage by percentile, 1981-2010, Males and Females. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotone for males in lower percentiles. Source: Survey of Income and Housing.

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.

2.3 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 2.1 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 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. Table 2.1 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 2.2 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.

That the income distribution is widening, but the skill premium is *not* driving the

	Log Skill Premium	
Year	**United States**	**Australia**
1982	0.42	0.42
1995	0.59	0.36
2003	0.64	0.37
2008	0.68	0.34

Table 2.1: 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).

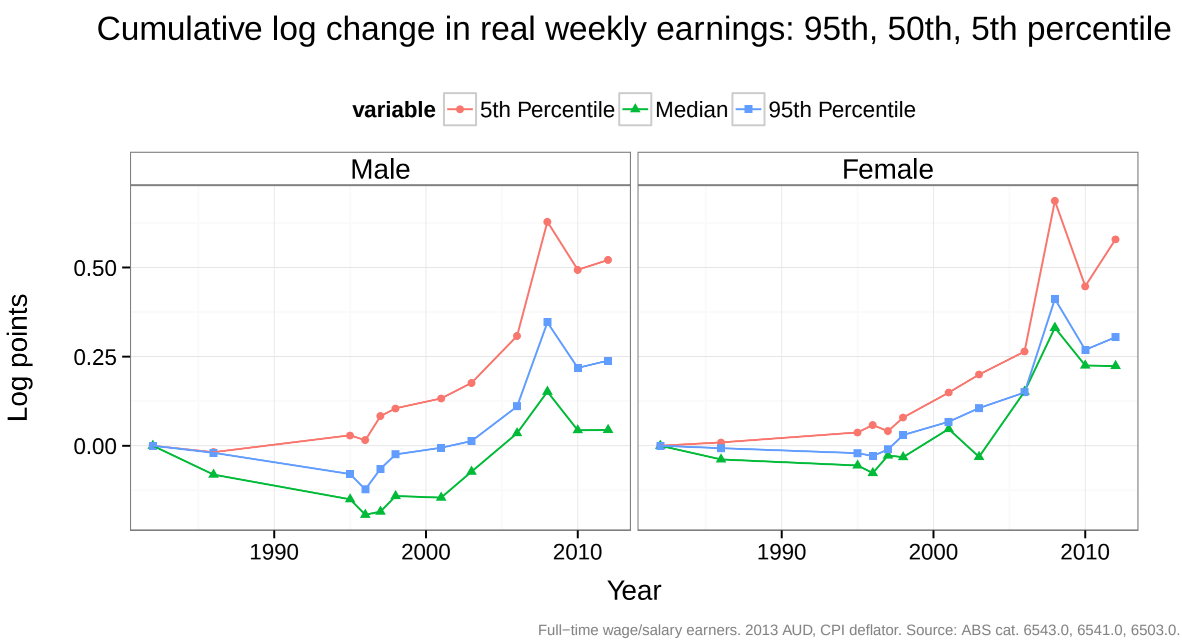

Figure 2.2: Cumulative log change in real weekly earnings, 5th, 50th and 95th percentiles, 1982-2010. Full-time workers whose main sources of income are wages and salaries are shown. Notice that real wage growth has been non-monotone for males in lower percentiles. Source: Survey of Income and Housing.

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, Levy, and Murnane (2003). Technological change may not be complementary to all types of labor; it may replace many types of labor entirely.

Chapter 3

ICT investment and Wage Shares

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 et al., 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.

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 it may appear to a human worker, is not yet possible with a machine. Under this definition, many occupations which we might colloquially consider 'routine'—such as stacking shelves or driving a taxi—require a degree of perception and motor control out of reach for a computer, and for our purposes are 'non-routine.' In these areas, for the moment at least, human workers enjoy a competitive advantage, and technology is not yet a substitute (Autor, Levy, & Murnane, 2003).

Thus computing capital is a complement to some kinds of task-performing labor, and a substitute for others. As Autor, Levy, and Murnane (2003) show, 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. Non-routine tasks, on the other hand, may improve, rather than replace, the efficiency of human workers. Indeed, as Borland et al. (2004) found by studying the computer knowledge of a cross-section of Australian workers surveyed in 1992, computer knowledge accrues a skill premium of around 10%. Likewise, Goos and Manning (2007) show a similar trend in the United Kingdom: between 1975 and 2003, they find an 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 most of Continental Europe (Goos, Manning, & Salomons, 2009).

The task approach departs from the standard neoclassical production function, which views aggregate economic output as a simple function of inputs such as capital and labor, but 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.

3.1 Model

To test this pattern for Australian data, we can augment (B.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:

$$Y = \left[(A_L L)^{\frac{\sigma-1}{\sigma}} + (A_M M + C)^{\frac{\sigma-1}{\sigma}} + ((A_H H)^{\mu} + C^{\mu})^{\frac{\sigma-1}{\mu\sigma}} \right]^{\frac{1}{\sigma-1}}. \tag{3.1}$$

Michaels, Natraj, and Reenen (2013) use a formulation similar to (3.1) 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.[1] To test these predictions, 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.

$$\Delta SHARE^S = \alpha_{CS} \log(C/Q)_{it} + \alpha_{KS} \log(K/Q)_{it} + \alpha_{QS} \log(Q)_{it}. \tag{3.2}$$

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, Levy, and Murnane (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'

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

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

3.1.1 Results

The results from estimating (3.1), given in Table 3.1, 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 (3.2). 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 3.1 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'

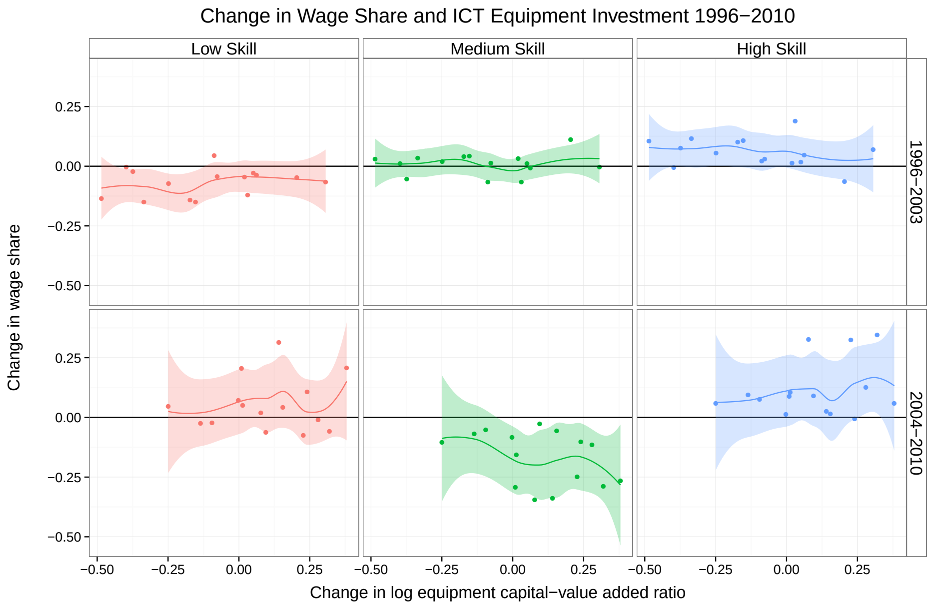

Figure 3.1: Change in wage share against change in log ICT electrical and electronic equipment capital ratio, by industry, Australia, 1996-2010. Fitted line comuted using LOESS regression and 95% confidence interval. See note for Table 3.1 for more details.

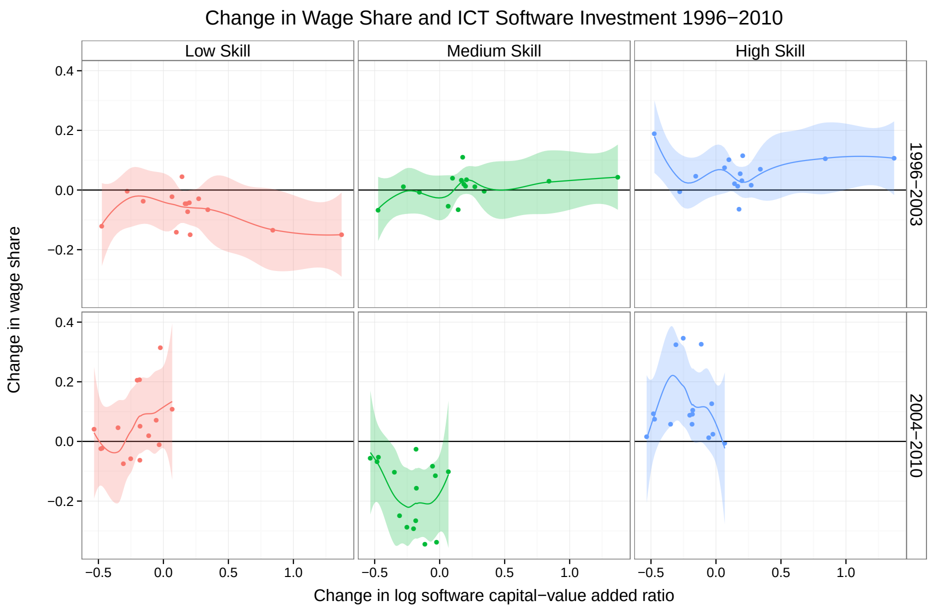

Figure 3.2: Change in wage share against change in log ICT software capital ratio, by industry, Australia, 1996-2010. Fitted line comuted using LOESS regression and 95% confidence interval. See note for Table 3.1 for more details.

Table 3.1: Wage Share Change Estimation Results: 1996-2010

	Dependent variable:								
	$\Delta SHARE^H$			$\Delta SHARE^M$			$\Delta SHARE^L$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δlog *equipment*	0.931								
	(0.699)								
Δlog *software*	−0.0001			0.454			−1.444		
	(1.625)			(1.369)			(1.303)		
Δlog *other capital*		0.653		−0.964*	−0.883**		0.328	0.095	
		(0.532)		(0.490)	(0.432)		(0.466)	(0.413)	
Δlog *value added*			−0.131	0.082		−0.025	−0.040		−0.010
			(0.537)	(0.440)		(0.441)	(0.419)		(0.414)
Constant	1.373	1.157	0.553	−0.343	−0.724	−0.077	0.228	1.273	1.193
	(1.613)	(1.113)	(1.138)	(1.376)	(0.903)	(0.935)	(1.309)	(0.864)	(0.877)
Constant	−0.049	−0.032	−0.013	0.014	0.035	0.019	−0.032	−0.088	−0.086
	(0.095)	(0.073)	(0.077)	(0.082)	(0.059)	(0.063)	(0.078)	(0.057)	(0.060)
Observations	112	112	112	112	112	112	112	112	112
R^2	0.023	0.017	0.004	0.038	0.037	0.0001	0.032	0.020	0.020
Adjusted R^2	-0.005	-0.001	-0.014	0.002	0.019	-0.018	-0.005	0.003	0.002
Residual Std. Error	0.395 (108)	0.394 (109)	0.397 (109)	0.323 (107)	0.320 (109)	0.326 (109)	0.307 (107)	0.306 (109)	0.306 (109)
F Statistic	0.830 (3; 108)	0.957 (2; 109)	0.231 (2; 109)	1.065 (4; 107)	2.096 (2; 109)	0.004 (2; 109)	0.874 (4; 107)	1.139 (2; 109)	1.112 (2; 109)
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).*

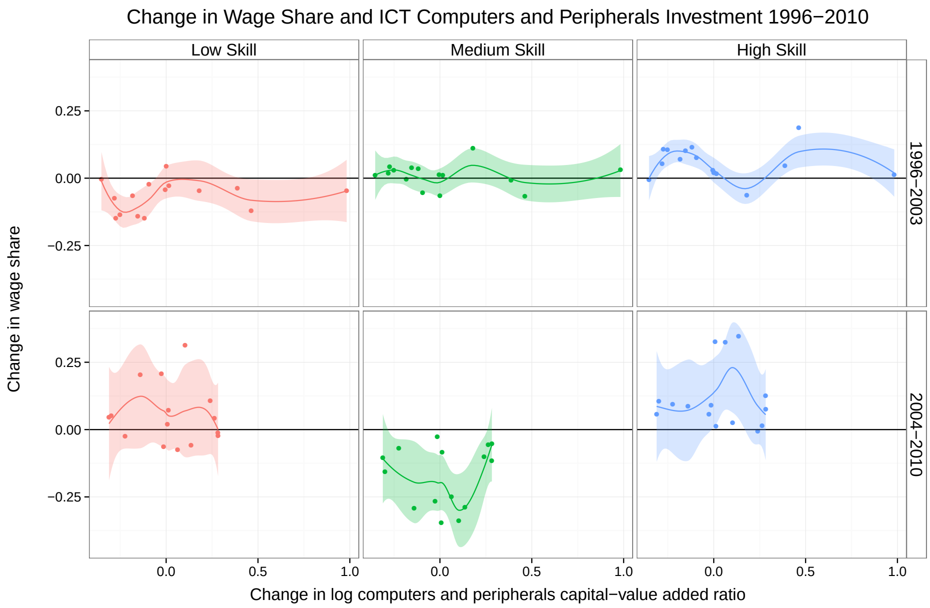

Figure 3.3: Change in wage share against change in log ICT computers and peripherals capital ratio, by industry, Australia, 1996-2010. Fitted line comuted using LOESS regression and 95% confidence interval. See note for Table 3.1 for more details.

view that occupational tasks, rather than other human capital variables, are important determinants of the evolution of the wage distribution.

3.2 Conclusions

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.

Chapter 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, Levy, and Murnane (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, Levy, and Murnane (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.'

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, Murphy, and Pierce (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 4.2.2, 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.[1] 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.

4.1 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

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

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

$$E\left[log(F_i)|\pi_f F_i \geq \pi_r R_i\right] = \mu_f + \frac{\sigma_{ff} - \sigma_{fr}}{\sigma}\lambda\left(\frac{log(\pi_f) - log(\pi_r) + \mu_f - \mu_r}{\sigma}\right) \tag{4.1}$$

for fishing, and

$$E\left[log(R_i)|\pi_r R_i \geq \pi_f F_i\right] = \mu_r + \frac{\sigma_{rr} - \sigma_{rf}}{\sigma}\lambda\left(\frac{log(\pi_r) - log(\pi_f) + \mu_r - \mu_f}{\sigma}\right) \tag{4.2}$$

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 (4.1) and (4.2) 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 (4.2) and (4.1) 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.

4.2 Empirical Approach

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, Fortin, and Lemieux (2011), is to adapt the simple linearly additive functional form of Welch (1969). Welch assumed that an individual's wage is determined linearly by the individual skills that worker possessed.

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

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

Where θ_{jt} is a 'base pay' term, 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.

4.2.1 Changes in the Wage Profile: A Direct Analysis

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:

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

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

4.2.2 The Decomposition Approach

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

$$\Delta = E[\ln y_m] - E[\ln y_f]. \tag{4.7}$$

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

$$\begin{aligned} \Delta_O &= E[X_m]'\boldsymbol{\beta}_m - E[X_f]'\boldsymbol{\beta}_f \\ &= \underbrace{E[X_m]'(\boldsymbol{\beta}_m - \boldsymbol{\beta}_f)}_{\Delta_S} + \underbrace{(E[X_m]' - E[X_f]')\boldsymbol{\beta}_f}_{\Delta_X}. \end{aligned} \tag{4.8}$$

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 (4.8) 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. The explanatory variables of interest in this case is a matrix of task content indexes, for each occupation. The procedure for constructing these indexes is described in the data appendix, Section A.2.2.

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 (4.8), but which decomposes changes in the αth quantile of the wage distribution, $q_\tau(F_Y)$. Such a decomposition was considered by Firpo et al. (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_S^τ:

$$\begin{aligned}\Delta_O^\tau &= q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=0}) \\ &= \underbrace{q_\tau(F_{Y_1|T=1}) - q_\tau(F_{Y_0|T=1})}_{\Delta_S^\alpha} + \underbrace{q_\tau(F_{Y_0|T=1}) - q_\tau(F_{Y_0|T=0})}_{\Delta_X^\alpha}\end{aligned} \tag{4.9}$$

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 (4.9), 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 (4.9) in a similar form as (4.8),

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

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

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

Importantly, Assumption 2 means that the set of occupational titles in both periods must be the same, even though many new types of occupational titles have been created since 1981-2. 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 3 (Ignorability)**.** *For* $T \in \{0,1\}$*, let* (T, X, ϵ) *have a joint distribution. Then, for all* $x \in \mathcal{X}$*,* ϵ *is independent of* T *given* $X = x$*.*

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

Most decompositions of the determinants of wages, including this one, follow the Mincerean 'human capital' approach, which suggests that the primary determinants of wages are investments in education and experience, which enhance productivity (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 4 is avoided by the linear functional form imposed by Assumption 1 (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.

4.2.3 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 (4.9) 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:

$$\begin{aligned}
\hat{\Delta}^{q_\tau} &= (\hat{\Delta}_{S,p}^{q_\tau} + \hat{\Delta}_{S,e}^{q_\tau}) + (\hat{\Delta}_{X,p}^{q_\tau} + \hat{\Delta}_{X,e}^{q_\tau}) \\
&= \underbrace{\left([\bar{X}_{01} - \bar{X}_0]\hat{\gamma}_{01}^{q_\tau} + \bar{X}_{01}[\hat{\gamma}_{01}^{q_\tau} - \hat{\gamma}_0^{q_\tau}]\right)}_{\hat{\Delta}_S^{q_\tau}} + \underbrace{\left(\bar{X}_1[\hat{\gamma}_1^{q_\tau} - \hat{\gamma}_{01}^{q_\tau}] + [\bar{X}_1 - \bar{X}_{01}]\hat{\gamma}_{01}^{q_\tau}\right)}_{\hat{\Delta}_X^{q_\tau}}. \qquad (4.10)
\end{aligned}$$

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

4.3 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.1.1 and A.2.2 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.

4.3.1 Survey of Income and Housing

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, 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.1.1).

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.

4.3.2 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.[2] 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 A.2.2.

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

[2] Some job information, including tasks and knowledge requirements are available in the ANZSCO and ASCO. However, these are not in a form that can be used for quantitative analysis: see Section A.2 for a discussion.

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 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`.[3]

4.4 Results

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 4.1 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 4.1: 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

[3]These scales are not completely independent. See Appendix Section A.2.2 for a discussion.

[4]Census data are used in Figure 4.1, 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.

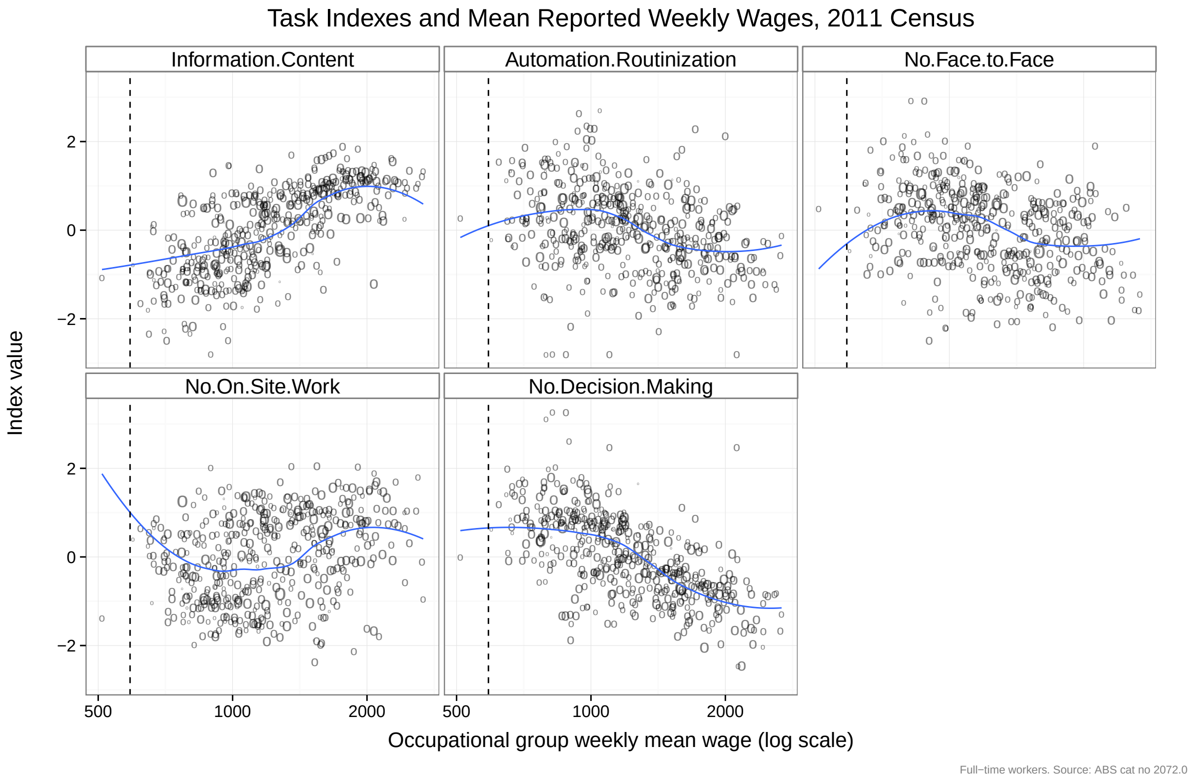

*Figure 4.1: Mean occupational weekly wage and task measure index values, at ANZSCO unit group (4-digit) level. The vertical dashed line is drawn at the level of the National Minimum Wage, of $589.30 per week. Census respondents reporting full-time work are shown. The loess regression line is weighted 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 A.1). Sources: ABS cat 2072.0, O*NET, US Dept of Labor.*

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 over time.

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 4.2.1 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 4.1 and 4.2, 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 4.2, 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 4.1 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 4.1 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 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 4.1, 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

Table 4.1: 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 4.2: 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.

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]

Figure 4.2 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 bottom 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 4.2 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,

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

[5]The results presented in Tables 4.1 and 4.2 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.

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

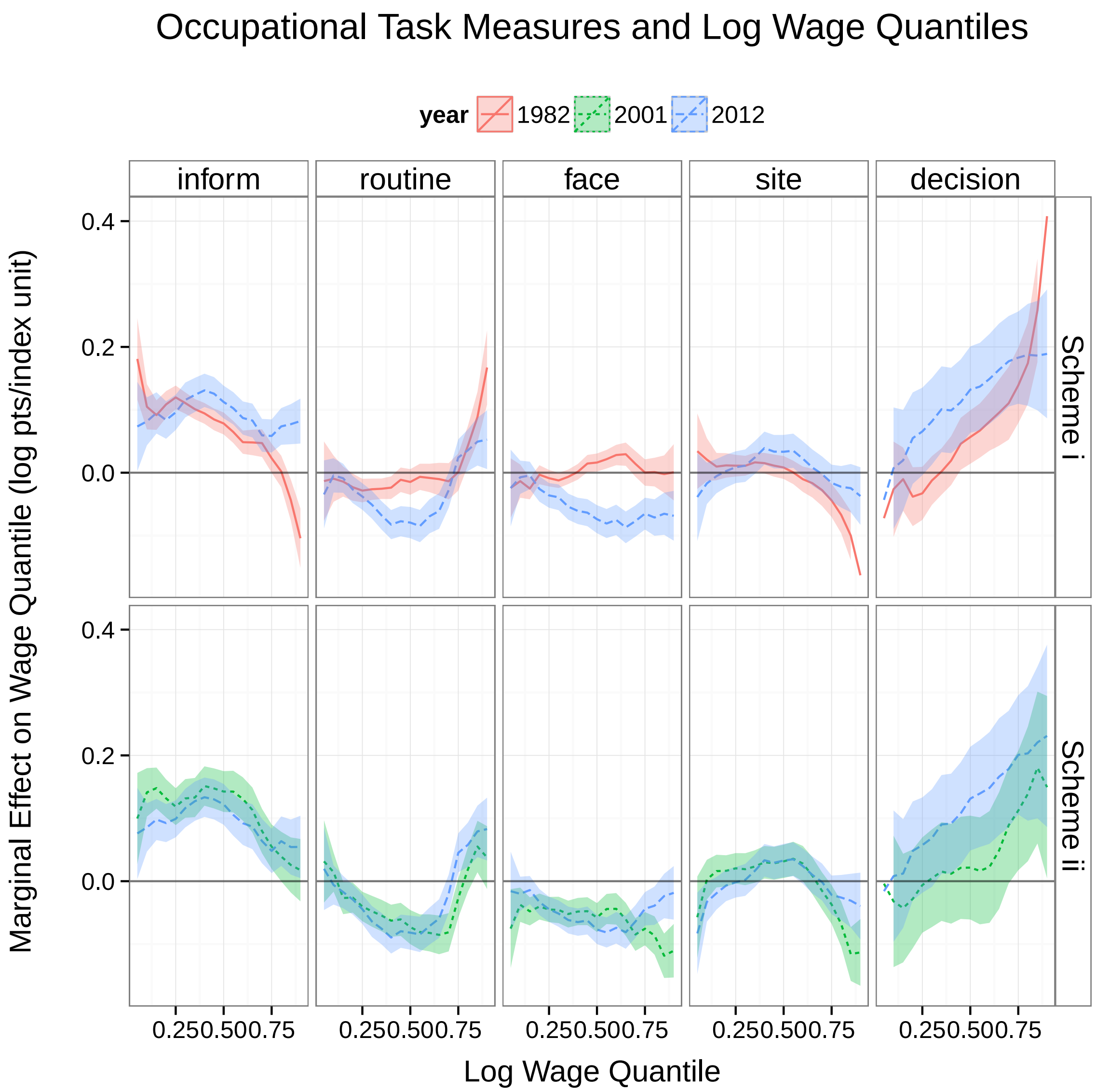

*Figure 4.2: Marginal log wage effect of task measures on log wage quantiles, 1981/82–2011/12 and 2000/01–20011/12, with shaded 95% confidence intervals. At any given quantile, overlap between the confidence band and the x-axis indicates a lack of statistical significance. The top row shows unconditional 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.*

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 of that task measure would increase. This change corresponds to the Δ_X term of (4.8). 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.

4.4.1 Decomposition Results

4.5 Conclusions

Chapter 5

Conclusions & Further Work

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Appendix A

Data

A.1 Income Surveys

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

A.1.1 Survey of Income and Housing, 1981-2012

The Survey of Income and Housing (SIH) is a hierarchical, clustered sample survey of income and expenditure patterns of the 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.1.2 Census

A.2 Occupational Data

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.

A.2.1 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.

A.2.2 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

The correlation between each job index is plotted in Figure A.2. 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 ($\rho = -0.276$).

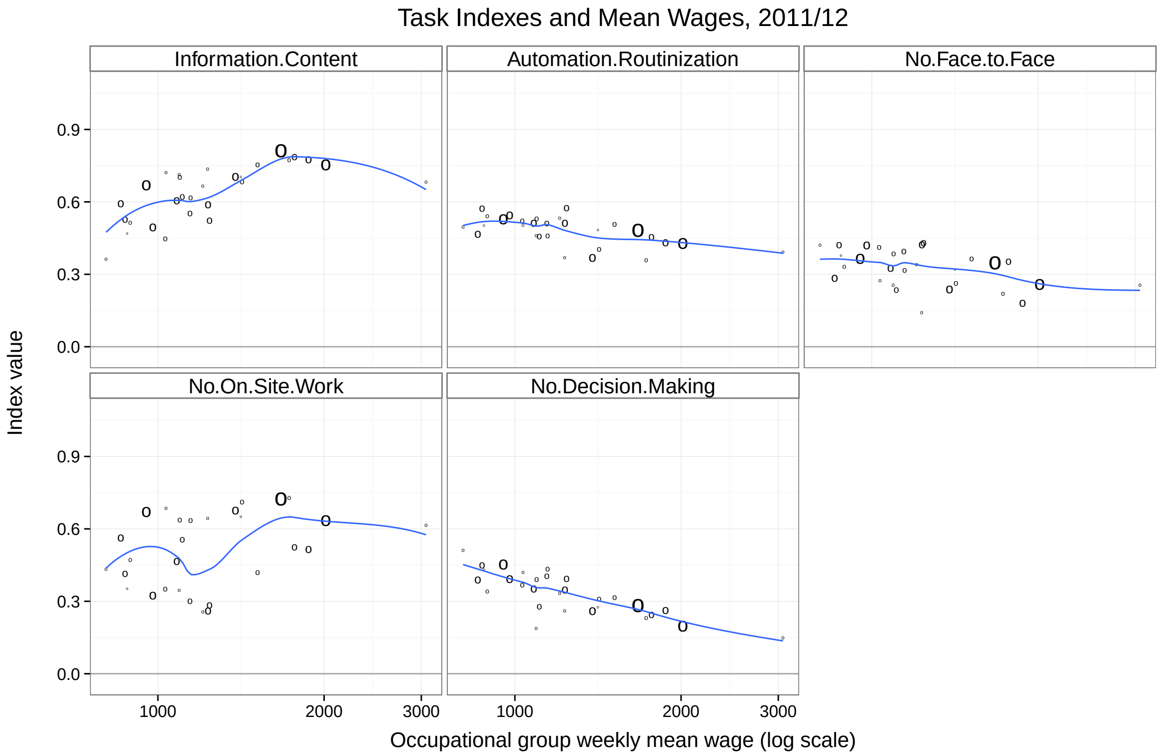

*Figure A.1: Mean occupational wage and task measure index values, using second combined grouping. Note the similarity of the observed trend to Figure 4.1, in which occupations have not been grouped. Census respondents reporting full-time work are shown. The loess regression line is weighted by population; circle areas are proportional to population for each occupation. Sources: ABS cat 2072.0, O*NET, US Dept of Labor.*

Correlation Plots: Derived Task Indexes

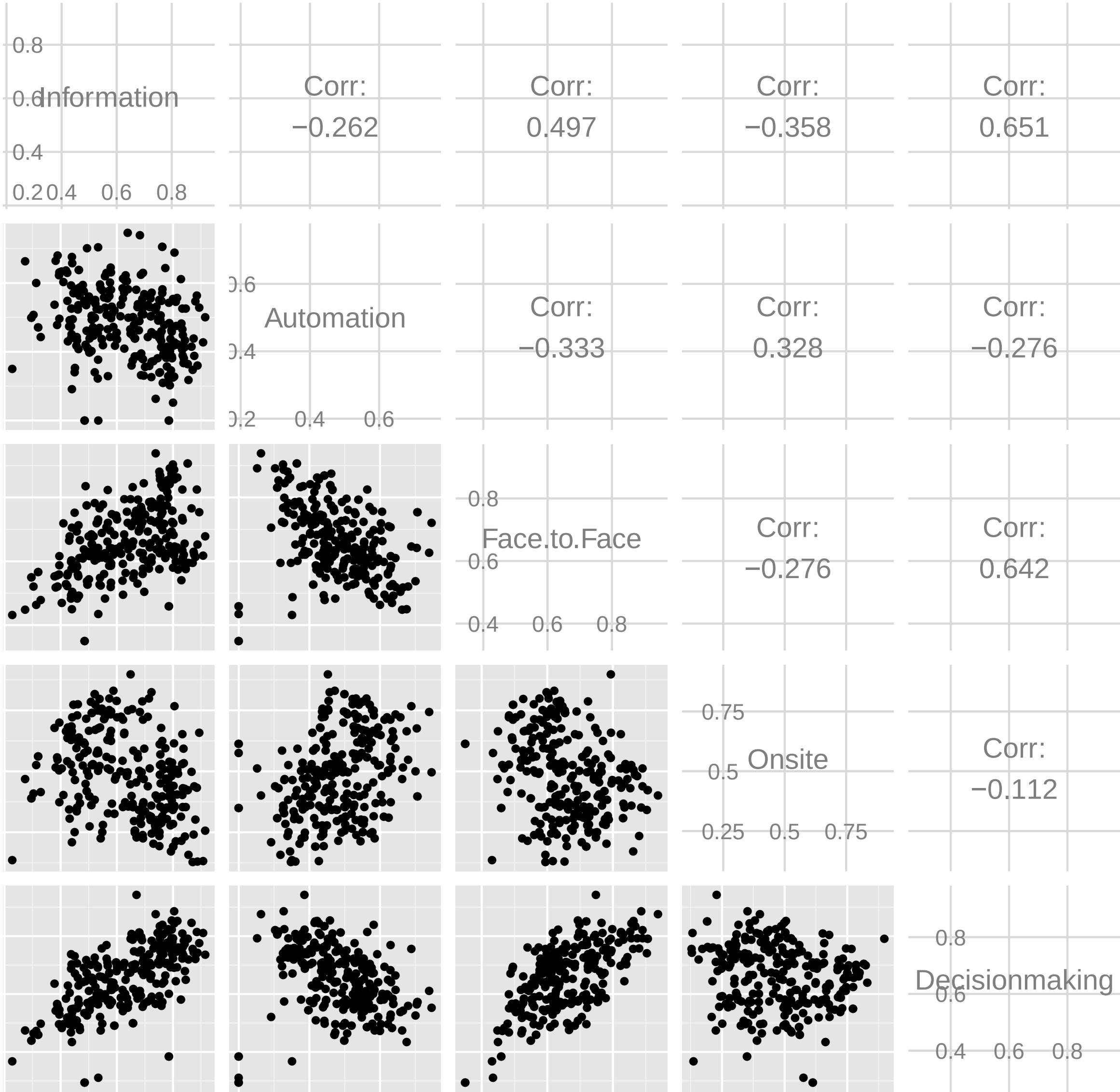

Figure A.2: Correlation plots: occupational task indexes for jobs at the ANZSIC 3-digit level.

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

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.

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

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:

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

And the comparative statics are—

$$\frac{\partial \theta_H}{\partial C} = \frac{\gamma H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-2} \left(\beta M (C+M)^\rho \left(C^\eta (C(-\eta) + C + M(\rho-\eta)) - C(\rho-1)H^\eta\right) - \alpha C^\eta (C+M)\right.}{C\left(\alpha (C+M) L^\rho + \beta M (C+M)^\rho\right)^2}$$

$$> 0$$

$$\frac{\partial \theta_M}{\partial C} = \frac{\beta M (C+M)^{\rho-2} \left(\alpha C(\rho-1) L^\rho \left(C^\eta + H^\eta\right)^2 + \gamma H^\eta \left(C^\eta + H^\eta\right)^{\rho/\eta} \left(C^\eta (C(\eta-1) + M(\eta-\rho)) + C\right.\right.}{C\left(H^\eta \left(\gamma \left(C^\eta + H^\eta\right)^{\rho/\eta} + \alpha L^\rho\right) + \alpha C^\eta L^\rho\right)^2}$$

$$< 0$$

$$\frac{\partial \theta_L}{\partial C} = -\frac{\alpha L^\rho \left(\beta M(\rho-1)(C+M)^{\rho-2} - \gamma C^{\eta-1}(\eta-\rho) H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-2}\right)}{\left(\gamma H^\eta \left(C^\eta + H^\eta\right)^{\frac{\rho}{\eta}-1} + \beta M (C+M)^{\rho-1}\right)^2}$$

$$\gtrless 0$$