The Australian labour market and the digital economy*

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Abstract

We review the impact of the digital economy on the Australian labour market. The main ways in which the digital economy can affect the labour market are catalogued; and illustrated with case studies on robots and the gig economy. Evidence on the effects of the digital economy in Australia is assessed, combining new empirical analysis with findings from existing studies. Three main labour market outcomes are considered: (i) the total amount of work; (ii) the type of work and skills demanded; and (iii) the labour share of income. We conclude with discussions of policy implications and lessons.

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1] Introduction

The times we live in are already being recognised as an era of major technological innovation. In a notable study Kelly et al. (2021) use United States patent data to identify three main waves of innovation since 1840:

'…from 1870 to 1880; 1920 to 1935; and from 1985 to the present.…The first peak corresponds to the beginning of the second industrial revolution, which saw technological advances such as the telephone and electric lighting. The second peak corresponds to advances in manufacturing, particularly in plastics and chemicals… The latest wave of technological progress includes revolutions in computing, genetics, and telecommunication.'[1]

The current wave of innovations revolves around developments in information technology (IT), which we take as our (broad) definition of 'the digital economy'. As with earlier major waves of innovation, how developments in IT will affect labour market outcomes has become a topic of on-going concern and debate. Analysis of earlier waves of innovation has found substantial impacts on workers and jobs.[2] What is also found, however, is that contemporary commentary on the effects of technological change often mixes a large portion of fancy with fact.[3]

In this paper we review the impact of the digital economy on the Australian labour market. We have three main objectives:

• first, to provide a framework for organising thinking about how the digital economy might potentially affect the labour market;
• second, to review available empirical evidence on the effects on labour market outcomes in Australia (including original work done for this paper); and
• third, to suggest policy implications and lessons.

Several broad themes emerge from our review. The digital economy is having a wide-ranging impact on the Australian labour market. Considerable, ongoing and steady adjustment has been occurring as a result: affecting the tasks workers do, the types of

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[1] Kelly et al. (2021) measure quality of patents based on the extent to which their content is: (i) distinct from previous patents; and (ii) similar to future patents. A 'breakthrough' patent is defined as one that falls in the top 10 per cent of the quality distribution among all patents in all years. Major waves of innovation are identified from an annual index of the number of breakthrough inventions granted in a year divided by the US population in that year.

[2] As just a few examples – replacement of hand-loom weavers by the power loom in the Industrial Revolution (Allen, 2018); the impact of steam power on mechanisation of manufacturing production in the second half of the nineteenth century (Atack et al., 2019); and automation of telephone operation in the 1920s to 1940s (Feigenbaum and Gross, 2020).

[3] Autor (2015) and Mokyr et al. (2015) describe commentary on major historical episodes of technological change in the United States. For Australia, see Borland and Coelli (2017, p.380).

jobs people are working in, the level of skills workers are bringing to the market, and the share of income earned by workers. But we find no evidence of any reduction in the aggregate amount of work. Nor does the labour market provide evidence that digital technologies have caused the pace of change to accelerate.

The paper is organised as follows. Section 2 describes the ways in which impacts of the digital economy on the labour market might occur. To illustrate, and as a window into recent international literature, section 3 presents case studies on the effect of robots and the gig economy on labour market outcomes. Section 4 assesses evidence on the impact of the digital economy on the Australian labour market. Three main labour market outcomes are addressed: (i) the total amount of work; (ii) the type of work and skills demanded; and (iii) the labour share of income. Section 5 considers how COVID-19 has affected the application of digital technologies and the consequences for the labour market. Section 6 evaluates policy implications of the digital economy. Section 7 concludes with some suggested lessons.

2] How the digital economy can affect the labour market

Effects on the Australian labour market from digital technologies can happen in a variety of ways. We classify the potential types of impacts according to where the effect of technology occurs:

i] How firms produce
ii] What firms produce
iii] Where firms produce
iv] How firms sell
v] How workers get jobs
vi] What skills workers need and how they get them
vii] Effects on workers' bargaining power
viii] Does the labour market affect technology?
ix] Policy-making and the labour market

2.i] How firms produce

<u>2.i.a] What happens to the demand for labour?</u>

The new canonical model of the role of labour in production has a firm's output depending on performance of a mass of tasks (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2020a). Each task can be completed by workers of different skill levels (for example, low or high) or by capital. These inputs are perfect substitutes but differ in their task efficiencies. Comparative advantage in task performance by labour is such that more skilled workers are allocated to more complex tasks. Capital substitutes for labour where it is the cheapest way to perform a task.

The development and adoption of improved or new technologies, that enable a firm to use capital to substitute for labour in performing a task, causes **displacement** of labour, generally referred to as automation. At the same time, those or other new technologies can cause **reinstatement** of labour in production, the creation of extra tasks in which labour is preferred to capital (Acemoglu and Restrepo, 2019, pp.3-4; Autor et al., 2021).[4]

As an illustration, Agrawal et al. (2019) model a decision-maker who must combine a prediction task and a decision task in order to take an action, such as hiring a new worker. The prediction task is to forecast some relevant piece of information, such as the relative productivity of job applicants. The decision task consists of other aspects associated with the action – such as collating information from the prediction tasks and judging how to make best use of the information. Suppose that recent advances in machine learning have increased the value of forecasts made using artificial intelligence (AI). This improvement in technology is likely to cause a displacement effect, the substitution of AI for labour doing prediction tasks. Examples of the displacement effect are substitution of labour by AI in evaluating job applicants or in disease diagnosis from radiological images. There may also be a reinstatement effect via creation of new decision tasks. A possible source of reinstatement effect is where a decrease in uncertainty due to AI-based prediction makes new decision tasks viable.[5]

The other impact on labour demand when a firm implements new technologies is via a **productivity** (or scale) effect. New technologies lower a firm's cost of operating and hence (where that cost saving is at least in part passed on to consumers) brings an increase in consumers' real incomes. That in turn can increase demand for the firm's output and therefore its demand for labour.

The impact on the total demand for labour at a firm which adopts a labour-replacing technology then depends on the aggregate of displacement, reinstatement and productivity effects.

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[4] Evidence in support of a direct impact of new technologies on the demand for labour is provided in recent studies showing a relation between patent activity and displacement and reinstatement of labour; for example, Autor et al. (2021); Webb (2020); Kogan et al. (2021).

[5] An historical example of the diverse ways in which technology change the structure of tasks is provided by Atack et al. (2019) in their analysis of the transition from hand to machine production in manufacturing in the United States in the late nineteenth century. They show that the set of transitions in jobs included: hand tasks destroyed; all tasks stay the same but are mechanised; single hand task divided into multiple machine tasks; multiple hand tasks combined into a single machine task; a new task structure mapping multiple hand tasks into multiple machine tasks; creation of new machine tasks.

The economy-wide effect on the demand for labour when a firm adopts a new technology is determined by the effect at the firm adopting the technology and by spill-over effects on other firms. Spill-over effects can be of two types. Firms which are competing in the same market with the adopting firm and do not adopt the new technology are likely to experience a fall in demand for their output and hence decrease their demand for labour. But firms in other markets may see increased demand for their output due to consumers having higher real incomes, and will therefore increase their demand for labour (Goos, 2018, pp.367-68). The increase in employment that results will be intensified by the tendency for new spending to be directed towards income-elastic services which are labour intensive (Baumol, 1967). An important way in which this effect is being manifested in recent years is through increased marketisation of services that were formerly home-produced – such as cleaning and gardening services; caring services; and meal production (Mandelman and Zlate, 2022, pp.356-57).

Adoption of labour-replacing technology can also affect a firm's relative demand for different types of labour - for example, labour with different skill levels or varying capacity to perform specific tasks. In thinking about how digital technologies might affect demand for different types of labour, a key insight is that tasks which can be codified into a programmable set of instructions are the most feasible to automate with digital technologies. These tasks are defined as 'routine' (Autor et al., 2003).[6] Workers in routine jobs are then at greatest risk of displacement due to automation. Whereas workers able to perform non-routine tasks cannot be as easily substituted for by capital, or may even benefit where new technologies create extra demand for their skills. This theory of the effect of technology on the relative demand for labour is described as **routine-biased technological change**.

New technologies which change the relative productivity of different skill levels of labour or of labour and capital, or affect the relative price of capital, can be a further source of changes in the relative demand for different types of labour. The theory of **skill-biased technological change** predicts that where technological change increases the productivity of high-skill relative to low-skill workers in performing a set of tasks, substitution of high-skill for low-skill workers should follow (Bound and Johnson, 1992). The theory of **capital-skill complementarity** predicts that where capital and high-skill labour are relative complements, a decrease in the price of capital will cause

[6] Autor et al. (2003, p.1283) define a routine task as 'methodical repetition of an unwavering procedure' that 'can be exhaustively specified with programmed instructions and performed by machines.'

capital deepening and an increase in the demand for high-skill relative to low-skill workers (Griliches, 1969).[7]

Because routine jobs are concentrated in middle-skill occupations, the routine-biased theory predicts that the adoption of new technologies will be associated with the phenomenon of 'job polarisation': a decrease in relative demand for labour to perform middle-skill jobs and increase in relative demand for labour in low-skill and high-skill jobs. Supporting evidence for job polarisation – using occupations to define skill - has been found in Europe, the US, Canada and Australia (Goos et al., 2009; Acemoglu and Autor, 2011; Green and Sand, 2015; Coelli and Borland, 2016).[8]

By contrast, the skill-biased and capital-skill complementarity theories predict that adoption of new technologies will cause a monotonic shift in labour demand towards high-skill and away from low-skill workers. These theories have also been found useful for explaining increases in the relative demand for more highly educated workers and an increase in the relative demand for high-skill workers in response to decreases in equipment prices (Katz and Murphy, 1992; Autor, Goldin and Katz, 2020; Krussell et al., 2000).

<u>2.i.b] Job design and organisational structure</u>

How tasks are bundled into jobs and occupations, and the organisation of jobs within a firm, can be affected by new technologies. There are several main reasons.

First, tasks that have been automated need to be removed from jobs; and new tasks need to be built into existing or new jobs. An example is the impact of AI on the job of a sell-side stock analyst: That job has adjusted to the improved capacity of AI to generate quantitative data on stock performance by shifting to involve spending more time obtaining 'soft' data and analysing stocks for which AI-based data are less available (Grennan and Michaely, 2020).[9]

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[7] In the task-based theory a firm's output depends on a set of tasks being completed, with each task being done entirely either by labour or capital. In the skill-based and capital-skill complementarity theories, production can be interpreted to depend on completion of a single task, which can be done using a combination of labour and capital. The former approach has the advantage of allowing complete displacement of labour from some stages of production, whereas the latter approach has the advantage of allowing output to be derived from labour working with capital equipment.

[8] Some research has also suggested an income-based explanation for job polarisation – see Comin et al. (2020).

[9] See also case studies of check processing by Autor et al. (2002) and valve manufacturing by Bartel et al. (2007).

Second, new technologies can change the returns to specialisation – and hence the task composition of jobs. For example, jobs may become more specialised where there is a large fixed cost in learning to work with a new technology, or alternatively, where a new technology increases labour productivity in doing individual tasks, the number of tasks bundled into a single job may be increased.

Third, the digital economy has improved measurement of performance and information flows within organisations. More information being more widely available throughout an organisation can, for example, increase the value of decentralisation in decision-making. Bresnahan et al. (2002) see developments in IT as part of a cluster of related innovations, most notably organisational redesign and product innovation.

2.i.c] Monitoring of workers

New technologies have made it easier to monitor workers. Examples are the need for workers to log into their employer's IT platform to commence work, thereby allowing their amount of time at work to be monitored; or wearables and apps that monitor workers' actions (Adams, 2018, p.357). Greater monitoring can increase workers' effort and compliance, but may also decrease job satisfaction and have privacy implications. In addition, there is the question of whether increased monitoring always improves efficiency or may just be a way for employers to obtain a larger share of the surplus from production (Acemoglu, 2021, pp.29-31).

2.ii] What firms produce

Developments in digital technology have underpinned many new types of consumer products. Substitution by consumers away from old products and towards the new products then generates job creation at firms producing the new products and destroys jobs at firms that produced the old products (or where the old and new are being produced at the same firm, extra job switching or churning of workers at that firm). Where the labour intensity of production or the types of labour skills required differ between the products, there can also be impacts on the total demand for labour and relative demand by skill. Examples of impacts of digital technologies on new product development, and hence on job creation and destruction, are the rise of the smartphones and associated demise of mobile phones made by Nokia; and the evolution from typewriters to word processing to PCs.[10]

[10] See for example https://en.wikipedia.org/wiki/The_Decline_and_Fall_of_Nokia

2.iii] Where firms produce

Digital technologies are expanding the range of locations from which labour can be supplied. Examples are the scope to work from home; the scope to provide labour services to larger geographic areas (such as tele-health being supplied to rural regions from cities); and the scope for offshoring of tasks such as clerical, sales and product support work.

The greater scope to work from home due to developments in digital technology is the aspect of the location of production that has received most attention recently (Productivity Commission, 2021). To what extent the greater scope to work at home translates into a change in the incidence of working from home will depend on workers' relative productivity at home versus at the office and their preferences for working in the alternative locations.

As an example, suppose that a new tool for virtual meetings enables a worker who previously was not able to complete the tasks required for their job outside the office to now work from home. In the case where the worker prefers working from home (for example, due to saving on commuting time and costs), where the workers' productivity is the same at home as at the office and where the employer also is able to reduce their costs of office space (Bloom et al., 2015), the efficient outcome would be for the worker to shift to doing their job from home. By contrast, if the worker is indifferent between working from home or the office (for example, if benefits to the worker from lower commuting time are offset by employers expecting longer work hours) and workers' productivity is lower at home due to effects of isolation and a decrease in teamwork and monitoring (Mas and Pallais, 2020, p.648), then the efficient outcome, even with the new technology for virtual meetings, would be for the worker to continue to be located at the office.

From society's point of view, a benefit of greater scope to work from home is increasing opportunities to engage in paid work for groups such as workers with a disability or with caring responsibilities. But equally, it may introduce new inequities – for example, because the scope to work from home differs between occupation groups; or due to the unequal impact on career development between members of a couple household when working from home intensifies inequity in the distribution of household tasks (Productivity Commission 2021, pp., 15, 80).

The ability to work remotely may increase the flexibility of timing of work. Examples are how the ability to log into a work server from home means being able to work at night or how the use of international locations for call centres allows 24-hour service. More generally as Freeman (2002, p.9) noted some years ago: 'As work becomes more intellectual – weightless – … the sharp division between work time, non-work-related web surfing, and leisure or home time itself becomes less meaningful.'

2.iv] How firms sell

Digital technologies are lowering the costs of distribution for many suppliers. Essentially these technologies have brought a substantial reduction in the cost of selling to customers outside the geographic region where a supplier is located. Examples are the scope for an online retailer to distribute to international markets; or for sports leagues and entertainers to broadcast their product globally.

Lower distribution costs have shifted the composition of retail demand towards technology-enabled methods of distribution; for example, from bricks-and-mortar retail outlets to online sellers such as Amazon. As well, network externalities associated with internet markets, the scope for online suppliers to sell a much wider range of output (the long tail phenomenon), and the greater capacity of large firms to pay the fixed cost of new technologies, has caused a superstar effect, an increasing concentration of retail sales with a small number of online suppliers (Levin, 2011, pp.8-10).

Similarly, lower costs of accessing international sports broadcasts, together with consumers' preference for viewing the highest quality of competition, has increased the share of broadcast and sponsorship revenue going to the top global competitions, such as the English Premier League (EPL) in football and the National Basketball Association (NBA) in basketball (Rosen, 1981; Szymanski, 2015, chapter 4).

Changes in distribution costs have affected the demand for labour differently depending on the type of market. In retail markets, the shift in demand to online suppliers and away from bricks-and-mortar is suggested to have caused an increase in relative demand for low-skill labour. As well, the concentration of online sales may have brought higher mark-ups and lower output, and hence caused a decrease in total demand for labour (for example, Autor et al., 2020; De Loecker et al., 2021). In sporting markets, where the labour of players constitutes the product being sold, there has been a substantial shift in demand towards the highest skill and most popular players (for example, Syzmanski, 2015, p.43; Futterman, 2016).

2.v] How workers get jobs

Internet job vacancy sites have provided a new way for workers and employers to match (Kuhn, 2014). The ease of posting job ads and the ease of making applications online means that internet job sites have by now largely (although not completely) substituted for other methods of posting vacancies. A key research question is whether matching efficiency – speed and quality of job match – has been improved. The answer might appear automatically to be yes, but there may be offsetting influences. For example, a lower cost of search causes job seekers to apply for more openings which creates difficulties for employers to evaluate an increased number of applicants; and as a method of job search, looking for work on the internet is likely to remain less effective than using personal contacts. Kuhn and Mansour (2014) report that prior to the mid-2000s unemployed job seekers searching using the internet had longer unemployment durations than those not using the internet, but that by the second half of the 2000s this had reversed. They attribute the reversal to an increased proportion of job advertisements being posted on internet sites and to internet job search having become less passive.[11]

Platform-based work has created a new way for workers to connect to customers and employers. This has mainly happened for the supply of services, such as transport, food transport, odd jobs and professional services. The new way of connecting allows extra opportunities for labour supply, due to the flexibility of timing of platform-based work. Some platform-based services may bring an increase in labour demand, substituting for activities households would otherwise have done themselves, such as delivery of take-away food. Other services are more likely to involve platform-based labour substituting for other labour, such as Uber and taxi transport.

2.vi] What skills workers need and how they get them

The digital economy is having an obvious effect on the skills required for work. The shift in composition of employment towards professional jobs has increased demand for workers with graduate qualifications. This is reflected in a substantial increase in the share of the Australian population with a university or college-level qualification. For example, the proportion of the population with Bachelors' degrees rose from 6 per cent in the early 1980s to 30 per cent in the mid-2010s (Borland and Coelli, 2017, Figure 2). It is also reflected in the types of skills sought, with development of analytic/cognitive, decision-making and management skills being paramount (Heath, 2020; Deming, 2021). In addition, where a faster pace of technological change increases the rate of skill obsolescence, this implies a greater need for on-the-job training and upskilling through formal training (Deming and Noray, 2020). Automation may, however, be reducing the scope for on-the-job learning by limiting workers' ability to gain a holistic appreciation of production processes (Acemoglu, 2021, pp.26-29).[12]

How skills are acquired is also being transformed by IT developments. These developments include computer-assisted learning; technology-enabled behavioural

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[11] As well as promoting genuine job connections, digital technologies (especially mobile phones) may also have increased the incidence of employment-related scams; see for example: https://www.9news.com.au/national/australia-fake-job-ads-scams-online-coronavirus-pandemic-months-emails-bank-accounts-phishing-details/714ee51e-7b27-44a8-bb36-463bb045cafd.

[12] Acemoglu (2021, p.28): '…a finer division of labor and the reallocation of some tasks away from humans can be cost-reducing, but to the extent that human judgment improves when workers gain experience from dealing with a range of problems and recognize different aspects of the problem, it may also come at a cost.'

interventions; and online education (Escueta et al., 2017). Computer-assisted learning has brought forth new pedagogies, with the promise of improvements in the productivity of education, such as through automated tailoring of teaching to students' progress in learning. Online provision of education brings greater flexibility in access for students – broadening who can enrol and making it easier to combine work with study. This in turn makes it profitable for providers to supply new types of courses, such as short courses for those in work. But online learning also generates trade-offs: there is consistent evidence that students learn more with face-to-face teaching than online; and students without internet access can be unfairly disadvantaged (for example, Altindag et al., 2021).

2.vii] Effects on workers' bargaining power

Workers' bargaining power may be affected by digital technologies. New labour-replacing technologies are suggested to have improved employers' outside options and hence lowered workers' bargaining power (Stansbury and Summers, 2020). Alternatively, increased concentration in online and platform-based markets may have raised employers' monopsony power; although there is little evidence of an increase in monopsony power in recent years (for a summary of recent evidence from the United States, see Grossman and Oberfeld, 2021, p.26). Potentially offsetting these influences is that digital technologies may lower the costs of organisation for unions or allow unions to run more effective campaigns for improvements in work conditions (Freeman, 2002; Jacoby, 2021).

2.viii] Does the labour market affect technology?

The relation between technology and the labour market may be two-way, with the state of the labour market influencing the development of new technologies. The theory of directed technical change specifies innovation and adoption of new technologies as depending importantly on labour costs, which in turn are influenced by labour supply.[13] With regard to the digital economy, Acemoglu and Restrepo (2022) argue that the pace of recent automation has depended on the age composition of the population, primarily a (demographically-imposed) lack of middle-aged workers whose comparative advantage is performing routine manual tasks.

[13] See for example Acemoglu (2002). Directed technical change has been argued to be an important source of innovation during the Industrial Revolution (Allen, 2009) and the rise of US manufacturing (David, 1979).

2.ix] Policy-making and the labour market

The digital economy is creating the same motivations for government policy interventions as earlier generations of technological change – such as ensuring that the workforce has the skills required to work with the new technologies and providing assistance to workers who are displaced from their jobs. Issues regarding the implications of the digital economy for the types of government policies that are needed are addressed in section 6.

The digital economy is also affecting how policy is made – for example, the data that policy-makers can draw on and the types of analyses they can do. Digital storage of information has increased ease of access to data and allowed the ABS and government departments to create new data sources that can be quickly brought to bear on policy-making. The National Skills Commission's Nowcast of Employment by Region and Occupation (NERO) is an example.[14] At the same time, increased computing power has made it feasible to analyse much larger and more complex data sets (for example, government administrative data). The series of papers that in recent years have come from the Treasury Micro-data unit, from the RBA on issues such as union effects on wages and from the Fair Work Commission on labour market transitions are illustrations.[15] An open question at present is whether the extra data and analysis has improved management of the labour market – with it being likely that a trade-off exists between the value of the extra information and costs of incorporating that information into decision-making.

3] Case studies

This section presents two case studies: overviews of the recent international literatures on the impact of robots and the gig economy on labour market outcomes. The case studies illustrate ways in which digital technology is affecting the labour market. They also provide a window to trends in international research on the labour market impacts of IT – for example, the evolution from studying economy-wide impacts of technological change to studying the effects of specific technologies at a firm and worker level.

3.i] Robots

Robots have been at the vanguard of fears that technology will bring an end to the world of work. *Rise of the Robots*, *Race Against the Machine*, *Why the Future is Workless* are just a few of the titles foretelling a future where humans will have much diminished

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[14] https://www.nationalskillscommission.gov.au/our-work/nero

[15] See for example, Andrews et al. (2019) and Andrews and Hansell (2019), Bishop and Chan (2019) and Yuen and Cuming (2021).

opportunities for work. Yet it is only relatively recently that empirical analysis has begun to provide an informed perspective on how robots do affect the labour market.

An industrial robot is defined as: 'an automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (Adachi et al., 2020, p.8). A robot can undertake myriad tasks: for example, instal and weld parts to car bodies, transport objects between locations and package goods for shipping (such as at warehouse distribution centres) and follow protocols to analyse samples in potentially hazardous settings (Dixon et al., 2020, p.5).

Decreasing prices and the capacity to apply robots to a wider set of production tasks, together with labour shortage, have brought a rapid increase in the adoption of robots in industrialised economies since the early 1990s.[16] In the United States and Western Europe a fourfold rise in the stock of industrial robots occurred between 1993 and 2007. Similarly, in Australia the stock of robots grew from 1,739 in 1993 to 8,016 in 2013. Growth in China was even faster; from having virtually no robots in 1995, by 2017 it had 339,970 robots, accounting for almost 20 per cent of the world stock. Global robot usage is concentrated within a subset of manufacturing sectors: 44.7 per cent in automotive, 23.6 in electronics, 11.5 per cent in metals and 10.8 percent in chemicals.[17]

Research on the labour market impact of robots has evolved rapidly in recent years. Appendix Table 1 summarises the literature. Early studies used industry-level data on robot stocks to examine the impact of exposure to robots on employment and wages. More recent studies are using firm-level data to study the effects of robots on the level and composition of employment and on wages, both at firms adopting robots and at firms competing with them.

The direct impact of adoption of robots by a firm is to displace workers doing routine tasks.[18] This displacement effect distinguishes robots from other types of technological

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[16] Graetz and Michaels (2018) find that quality-adjusted robot prices in 2005 were about one-fifth of their level in 1990. Dixon et al. (2020, p.5) describe how advances in speech, vision and prediction have allowed robots to perform tasks that are more cognitively complex and require greater manual dexterity. Acemoglu and Restrepo (2021) for the United States and Cheng et al. (2019) for China find that robot adoption is related to ageing workforces.

[17] Data for the US and Western Europe are from Acemoglu and Restrepo (2020b, p. 2189) and for China and the industry-level from Cheng et al. (2019, pp.73-75). Australian figures are taken directly from the International Federation of Robotics (IFR) database: https://ifr.org/. Squicciarini and Staccioli (2022) also document how robotics patents have increased steadily since 1978 and especially quickly in the past decade.

[18] Analysis of patent data by Squicciarini and Staccioli (2022, p.29)) finds that highly-exposed occupations to substitution by robots predominantly include a range of low- to high-skill blue-

change – such as capital deepening – which increase labour demand (Acemoglu and Restrepo, 2020b). How robotization affects economy-wide employment depends on the direct displacement effect and a whole set of other adjustments – within the firm adopting robots; within the product market in which that firm competes; at firms in other product markets; and in labour supply.

Firms which adopt robots are found in most studies to experience an increase in total employment following that event. Although workers doing lower-skill routine manual jobs are displaced by robots, this is more than offset by growth in employment of other types of workers, such as high-tech and managerial. The increase in total employment is partly due to lower costs following robotization, which brings a positive scale effect and can give rise to reshoring of production activities. But it is also partly from a selection effect associated with adopting firms having higher historical output growth – so that the causal effect of robot adoption on total employment is less clear.

What happens to economy-wide employment also depends on adjustment at other firms. Non-adopting firms competing in the same product market with adopting firms are found to experience a decrease in employment.[19] But employment at firms in other industries (such as business services) is likely to increase due to robotization.

Cross-country differences in the impact of robotization on employment appear to depend on country-specific factors that affect the relative sizes of displacement and reinstatement effects. For example, whereas for the United States Acemoglu and Restrepo (2020b) find that one extra robot per 1000 workers lowers employment by 0.2 per cent, for Japan Adachi et al. (2020) find a positive effect on total employment, which they attribute to a large scale effect, explained by Japan being a major exporter of manufactured output.

The decrease in demand for workers doing routine tasks has been manifested in less inflow of the young into those jobs (who instead switch to other occupations); and in layoffs of older workers (who on average find it difficult to gain re-employment) (Dauth et al., 2021; Cortes et al., 2020).

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collar jobs – such as delivery and cleaning jobs in the service sector and a range of shopfloor and warehouse jobs.

[19] Faber (2020) also shows that the negative impact on non-adopters can extend across national borders: the increased adoption of robots in the US from 1990-2015 is shown to reduce export-producing employment in Mexico.

3.ii] Gig economy

At the fore of recent debates on the future of work is how the gig economy might reshape labour markets. The gig economy broadens access to employment and can increase flexibility in timing of labour supply. But its location outside the existing regulatory framework for standard employment has brought concerns that gig economy workers are not adequately protected against exploitation.

There are alternative definitions of gig work, which mainly differ in the scope of activities included. A narrow definition is that gig work occurs where the supplier of labour is an independent contractor who uses mobile apps or websites to connect with customers/employers. Broader definitions go beyond platform-based work and include other categories of workers.[20]

In Australia, the main evidence on the incidence and impact of gig work, using the narrow definition of platform-based work, is from a special purpose household survey undertaken in early 2019 by McDonald et al. (2019). That survey found 7.1 per cent of the population had offered to work on a digital platform in the past 12 months, although at the time of the survey only about 0.2 per cent were doing full-time gig work and entirely reliant on that source of income. Gig work was concentrated in transport and food delivery (18.6 per cent), professional services (16.9 per cent) and odd jobs (11.6 per cent).

Measures of the incidence of platform-based gig work in the United States have been derived from financial transactions data and tax records. These studies have concluded that: (1) About 1.5 per cent of a sample of checking account holders were involved in gig work in 2018; but a much larger proportion, 4.5 per cent, had been involved at some time in the past 12 months (Farrell et al., 2019a, 2019b); (2) About two-thirds of gig employment is in the taxi and limousine services industry (Abraham et al., 2019; Collins et al., 2019; Farrell et al., 2019a); and (3) Growth in participation has been driven by workers for whom the gig economy provides a secondary source of income (Collins et al., 2019).

[20] An example of the narrow definition is that adopted by the Fair Work Commission: 'The gig economy uses mobile apps or websites to connect individuals providing services with consumers. You may also know the gig economy as the platform or app economy, the sharing economy or the on-demand workforce'; https://www.fairwork.gov.au/find-help-for/independent-contractors/gig-economy). An example of the broader definition is Mas and Pallais (2020, p.633): '…we use "gig jobs" to refer broadly to independent contractor and freelance work. Electronically mediated gig employment, which refers to work on platforms like Uber or Upwork, is a type of gig employment.'

Using a broader definition of gig work, based on alternative work arrangements, encompasses a larger proportion of workers. A commonly-adopted approach defines gig work as consisting of temporary help agency workers, independent contractors and on-call workers. For Australia, these workers made up 14.0 per cent of employment in 2008 and 13.9 per cent in 2019.[21] For the United States, the proportion of the workforce with alternative work arrangements has also been relatively constant over time: 10.1 per cent in 1995 and 10.5 per cent in 2017 (Katz and Krueger, 2019, p.412). Adopting an even broader definition that includes anyone currently engaged in paid informal work or side jobs (thereby including work done as a secondary job) increases the proportion of gig economy workers in the United States in 2015 to 32.5 per cent (Bracha and Burke, 2021).

Most knowledge on gig work is from analyses of specific markets; thus far primarily for Uber drivers. Alexander et al. (2022) use administrative and survey data to describe the labour market for Uber drivers in Australia.[22] Uber drivers' total hours of work and driving schedules exhibit substantial heterogeneity and week-to-week variation. Drivers are more likely to be using Uber to earn supplemental income than as their main source of income. Drivers for whom Uber provides a supplemental source of income tend to have higher incomes after joining Uber and express above-average levels of job satisfaction. By contrast, drivers who are looking for other work have lower incomes after joining Uber and express below-average levels of job satisfaction. Average hourly earnings (excluding commuting time and after costs) of Uber drivers in Sydney in 2018 were $23.65, about 25 per cent below the average for all casual employees in Australia.

A major theme of analyses of gig work has been the trade-off between the benefits of flexibility and scope to earn extra income versus the costs of lack of standard minimum conditions. Gig workers do appear to value the flexibility of being able to integrate work with other activities and to choose their timing of work. For example, a majority of Uber drivers in Australia express a preference for flexible over fixed hours. It is important to note, however, that in this regard they are very much a self-selected group, with recent studies finding that most workers do not place a high value on flexibility (Mas and Pallais, 2017). The opportunity to earn extra income can also provide a benefit from gig work, especially where it is in response to onset of financial distress, and hence a way to smooth income.[23] The main drawback of gig work is the worker's

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[21] For a general discussion of non-standard work in Australia, see Lass and Wooden (2020).

[22] Other studies of the labour market for Uber drivers are for the United States (Hall and Krueger, 2018; Hyman et al., 2020), London (Berger et al., 2018), France (Landier et al., 2016) and Egypt (Rizk, 2017). See also Berg and Johnston's (2019) critique of the Hall and Krueger study; and a response by Hall and Krueger (2019).

[23] Studies for the United States have found that financial distress is a major motivation for drivers commencing with Uber (Koustas, 2019; Jackson, 2019).

status as an independent contractor. The worker is not covered by a minimum wage and does not receive superannuation contributions or paid leave in case of illness. Other potential negative consequences from gig employment are that the individual doing the work may be trading off a short-term increase in income for a reduced likelihood of future employment (Jackson, 2019); and in the case of Uber, other workers such as taxi drivers may suffer a decrease in business (Berger et al., 2019).

4] Impacts of the digital economy on labour market outcomes in Australia

This section presents an overview of empirical evidence on the effects of the digital economy on the Australian labour market. Three main aspects of labour market outcomes are considered:

- The total amount of work;
- The type of work and skills demanded; and
- The labour share of income.

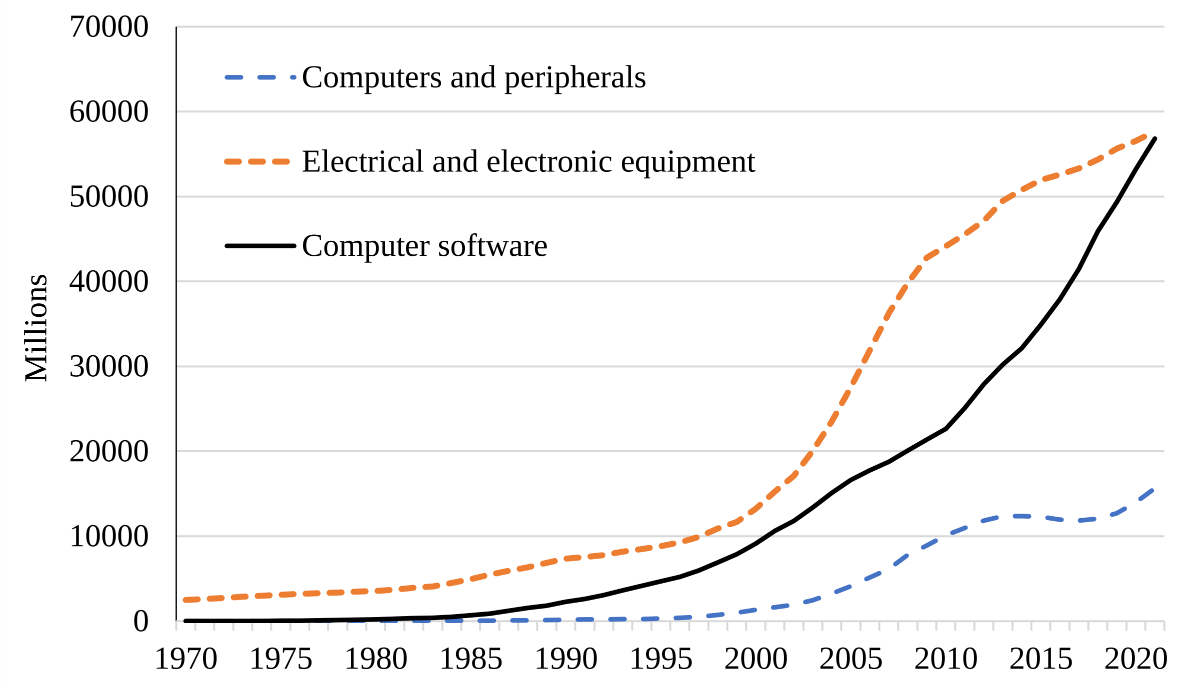
Evidence from existing studies is reviewed; and we also report findings from new empirical analyses.

4.i] The use of IT in production

Rapid growth has occurred in the use of information technology (IT) in Australia in recent decades. Figure 1 shows the net capital stock of computers, software and electronic equipment from 1970 onwards. The use of computers and IT in Australia began to increase from the early 1980s, and then rose much more rapidly from the mid-1990s onwards. Since the early 2010s, the pace of growth in the net capital stock of software has increased further, while the value of the stock of computers and peripherals has stabilised. The share of the net capital stock accounted for by computers and software has also risen steadily. In 1980 they were just 0.3 per cent of the total net value of the capital stock of machinery and equipment, then rose to 1.1 per cent in 1990, 3.4 per cent in 2000, 6.2 per cent in 2010 and 9.4 per cent in 2020.[24]

[24] Data from ABS, Australian System of National Accounts, Tables 56 and 69. What we define as the share of computers and software in the net capital stock of machinery and equipment equals the net capital stock of computers and software divided by the net capital stock of machinery and equipment plus the net capital stock of software.

Figure 1: Net real capital stock of computers, software, and electronic and electrical equipment, Australia all industries, 1966 to 2021 (June)



Note: Values are expressed in 2012-13 dollars.
Source: ABS, Australian System of National Accounts, catalogue no.5204.0, Table 69.

4.ii] Total amount of work

The recent wave of interest in the digital economy was initially focused on the idea that we might be about to see 'the death of work'. The nature and pace of take-up of digital technologies, some believed, would cause a substantial decrease in the total amount of work available.[25] Yet, there was little evidence at the time, and little evidence today, that this outcome is occurring.

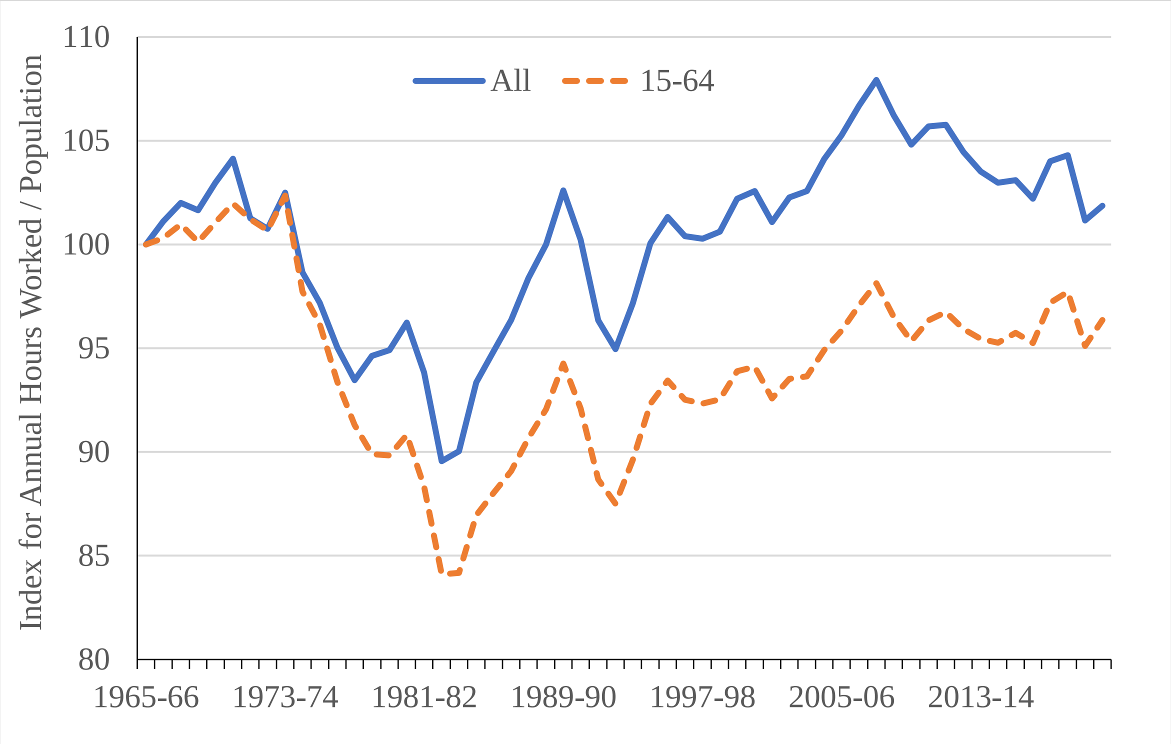
Figure 2 shows total annual hours worked per capita in Australia, from 1965/66 to 2020/21. This is a measure of the amount of work available on average for each member of the population in Australia. Alternative population definitions are used to derive the per capita measure: all population and population aged 15-64 years.

The main impression is the relative constancy of annual hours worked per capita over the long run, with the only variation being cyclical ups and downs. Certainly, no secular

[25] See Borland and Coelli (2017, pp.377-78) for examples. Frey and Osborne (2017) predicted in the early 2010s that 46 per cent of jobs in the United States were at high risk of automation in the next 10 to 20 years. For a critique of their analysis, see Coelli and Borland (2019).

decline in annual hours worked is observed with the rise of the application of IT in production processes from the early 1990s onwards.

Figure 2: Annual hours of work per capita, Australia, 1965/66 to 2020/21



Sources: (1) (a) All population: 1965 to 2010 (December): Butlin, Matthew, Robert Dixon and Peter Lloyd (2014), 'Statistical Appendix: Selected data series, 1800-2010', in S. Ville and G. Withers (eds) Cambridge Handbook of Australian Economic History (CUP), Table A2; 2011 to 2020 (December): ABS, Australian Demographic Statistics, Table 4; (b) Population aged 15 to 64 years: 1965-68: Commonwealth Bureau of Census and Statistics, The Labour Force 1964 to 1968, Table 4; 1969 to 1977: ABS, Labour Force Australia, catalogue no. 6203.0; 1978 onwards: ABS, Labour Force Australia, Table 18; (2) Annual hours worked: (a) Total employment: 1978 onwards: ABS, Labour Force Australia, Table 1; 1966-1977: ABS, Labour Force Australia Historical Summary 1966 to 1984, Table 1; 1965-66: Commonwealth Bureau of Census and Statistics, The Labour Force 1964 to 1968, Table 2; (b) Average hours worked by persons employed: 1991 onwards: ABS, Labour Force Australia, Detailed, Table 09; 1984 to 1990: ABS, Labour Force Australia 1978 to 1995, 6204.0; 1969 to 1983: ABS, Labour Force Australia, 6202.0, Assorted tables; 1965 to 1968: Commonwealth Bureau of Census and Statistics, The Labour Force 1964 to 1968, Table 21.

The implication is that the displacement effect of technological change has been consistently offset by reinstatement and productivity effects; or that other factors – such as increased marketisation of services formerly produced by households (for example, caring and meal production) - have offset what would otherwise have been a negative effect of technology on total employment.

Support for the conclusion that the effects of technological change on total employment have been offsetting comes from a study by Autor and Salomons (2018). It examines the impact of technological change on total employment using data for 28 industries in 19 countries (including Australia) for 1970-2007. The study finds that the negative displacement impact of technological change was more than offset during this period by productivity benefits (deriving from cheaper inputs from suppliers) and increased final demand.

4.iii] Changes in demand for labour by task and skill

What developments in digital technology undoubtedly have done is to change the relative demand for different types of labour. First, new technologies change the relative demand for labour according to its ability to perform different tasks. For digital technologies this impact has been investigated by looking at the relation between changes in occupation-level employment and the degree of routinisability of the tasks undertaken by workers in those occupations. Second, where workers with different skill levels have comparative advantages in completing different tasks, changes in task-level demand for labour can imply changes in relative demand for workers by skill. The main way in which this impact has been investigated is by associating skill with workers' highest level of education attainment.

In the next three sub-sections, we report evidence for Australia on the impacts of technological change on task-level labour demand and on the demand for labour by skill. The first sub-section describes changes in occupation-level employment, with occupations organised into categories depending on the routinisability of the tasks they require to be performed. The following sub-section presents new analysis for Australia on the dynamics of adjustment to changes in the occupation composition of employment. The final sub-section presents new estimates of the impact of technological change on the relative demand for labour by skill (education attainment).

4.iii.a] Changes in the demand for labour by task

Empirical analysis of the impact of new technologies on the relative demand for labour to perform tasks that differ in their degree of routinisability has used two main approaches (Autor, 2013). The first method distinguishes occupations based on whether they involve tasks that are primarily routine or non-routine. Usually this is also done with a further split between occupations according to whether they are intensive in cognitive or manual tasks. This gives four possible categories of occupations: routine cognitive; routine manual; non-routine cognitive; and non-routine manual. Changes in employment between these categories are compared to test how relative demand has shifted between occupations that are intensive in routine and non-routine tasks (Autor et al., 2003).[26] The second method is to create a measure of the 'routine intensity' of occupations, based on descriptions of tasks in sources such as the Dictionary of Occupation Titles or O*NET (Autor and Dorn, 2013). This allows changes in employment according to the degree of routineness of the tasks in an occupation to be tracked.

Table 1: Classification of occupations by routine intensity

	Routine	**Non-routine**
Cognitive	Office / Administration Sales	Managers Professionals Technicians
Manual	Production Operators / Labourers	Protective service Food / Cleaning Personal service

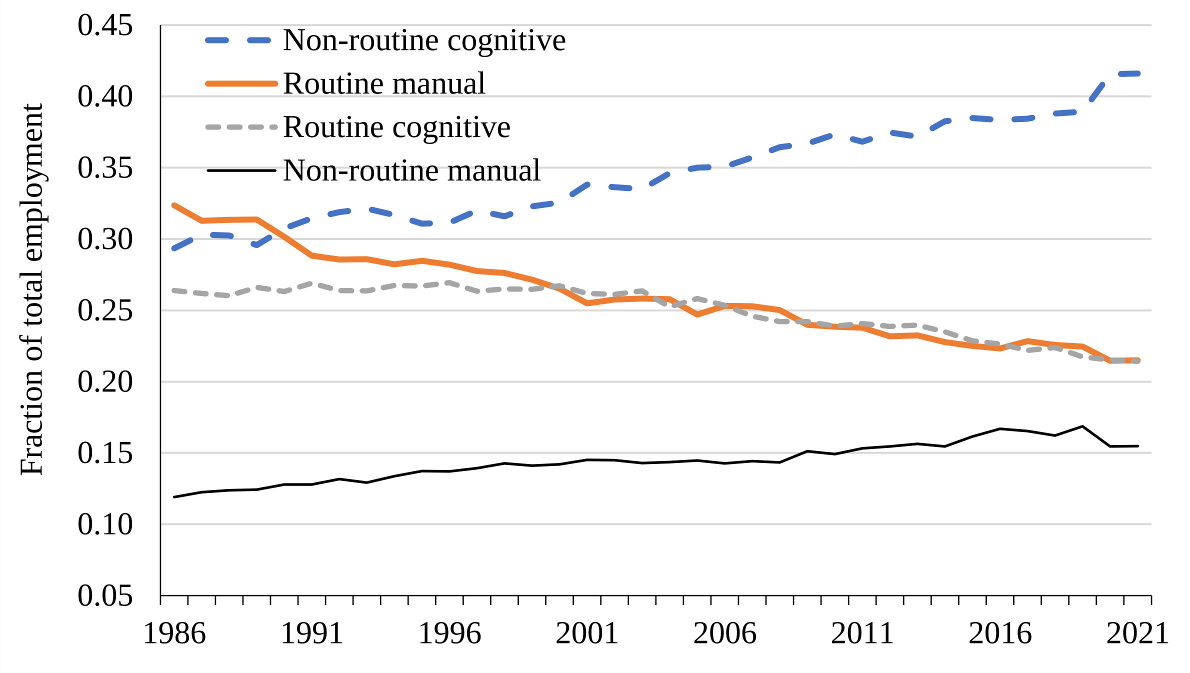
We describe changes in the composition of employment in Australia using the first method.[27] Figure 3a shows the shares of total employment in the four occupation categories from 1986 to 2021. The categories are constructed using employment in 4-digit occupations. We classify the 4-digit occupations into ten major occupation groups; and then assign those ten groups to the four occupation categories as shown in Table 1, following Acemoglu and Autor (2011). Figure 3b shows the annual per cent change in employment for the 10 major occupations ordered by skill level, over a longer period from 1971 to 2016. The ordering of occupations by skill level follows Acemoglu and Autor (2011).[28] Support for applying the classification for Australia is presented in Appendix Figure 1, which shows the relative intensity of abstract, manual and routine tasks in each of the four occupation groups.

[26] Note that recent research for the United States finds that there is also substantial reallocation of labour from routine to non-routine tasks within detailed occupation categories – see Atalay et al. (2020) and Freeman et al. (2020).

[27] For an application of the second method, see Coelli and Borland (2016).

[28] For alternative approaches to ranking the 10 occupation groups by skill level see Coelli and Borland (2016, pp.5-7).

Figure 3a: Share of employment by type of job, Australia, 1986 to 2021 (August)



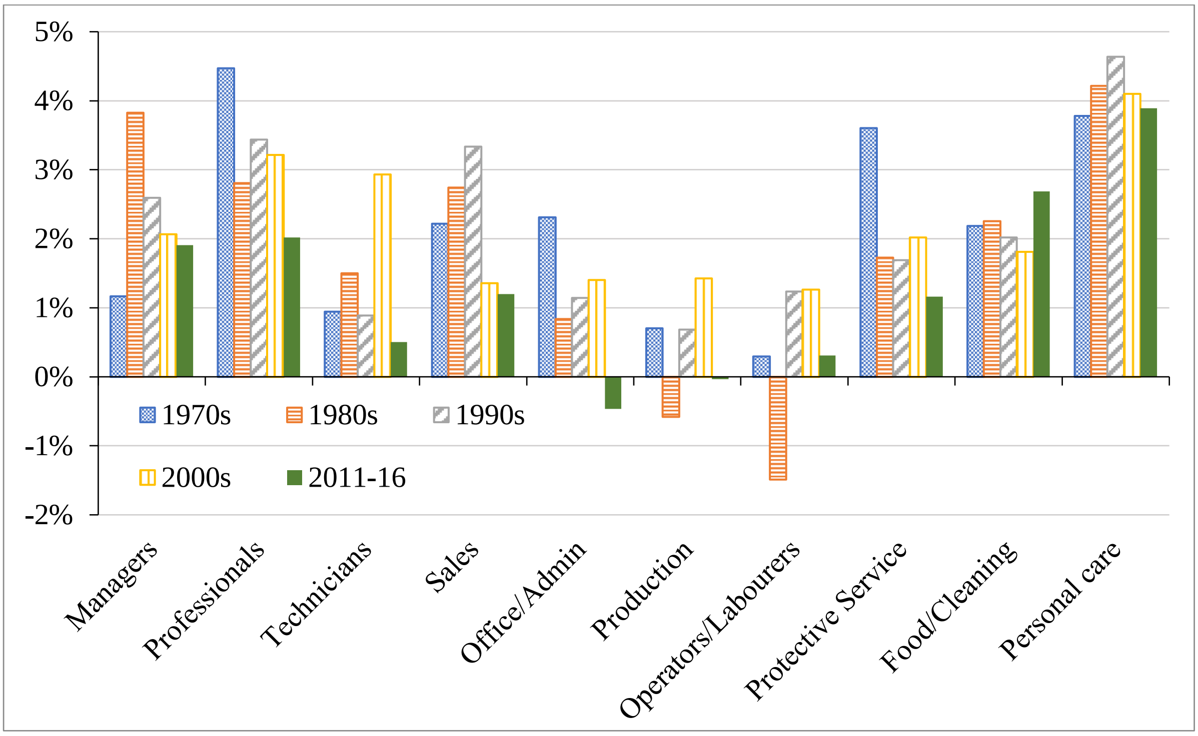
Source: ABS, Labour Force Australia, Detailed, EQ08. See Appendix Table 2 for assignment of 4-digit ANZSCO occupations to the 4 occupation groups.

Figure 3a reveals strong trends in the occupation composition of employment in Australia since the mid-1980s. The share of employment accounted for by routine manual occupations has consistently declined, falling by 10.9 ppts from 1986 to 2021. The routine cognitive share was constant until the early 2000s, after which time its share decreased by 5.0 ppts. The shares of employment in non-routine cognitive and non-routine manual occupations have both grown, by 12.3 ppts and 3.6 ppts respectively. The rates of change in all occupation groups have been relatively constant from the mid-1980s onwards, with the only exception being a slight acceleration in the shift towards non-routine cognitive employment from the mid-2000s.[29]

Figure 3b shows that the trend evident in the composition of employment from the mid-1980s – away from routine employment and towards non-routine employment - was already underway in the 1970s. It can also be seen that the ordering of occupations by skill level implies that routine occupations are located in the middle of the skill distribution, non-routine cognitive occupations at the top of the distribution and non-routine manual occupations at the bottom. This illustrates how the trends in the occupational composition of employment have been associated with the phenomenon of job polarisation: with growth in employment in high-skill non-routine cognitive occupations and in low-skill non-routine manual occupations, and little change in employment in the middle-skill routine occupations such as production and operators/labourers.

[29] See also Heath (2020).

Figure 3b: Per cent changes (annualised) in employment by occupation, 1971-2016, Australia



Sources: ABS customised tables, Australian Censuses, 1971–2016, occupations defined at four-digit level prior to grouping, all employed individuals, excluding agricultural and military occupations.

4.iii.b] How adjustment to changes in the composition of employment happens

Underlying the changes in the occupational composition of employment is a dynamic process of adjustment. For example, consider the decline in the share of employment in routine jobs. This could have happened either due to a faster rate of outflow of existing workers from those jobs or a slower rate of inflow of new workers.

Identifying the sources of adjustment can have important policy implications. To illustrate, we continue with the example of a decrease in the share of employment in routine jobs. Suppose the adjustment happens via a faster rate of outflow of older workers from routine jobs to non-employment. That may indicate a problem that older workers, displaced by new technologies, are not able to regain employment. Alternatively, suppose adjustment happens via a slower rate of inflow into routine jobs by younger workers, who seem instead to be moving into non-employment. This would suggest a different problem: that young people with skills suited to employment in routine jobs are being disadvantaged by the shrinking opportunities for employment in those jobs.

In what follows we present preliminary findings from a flows-based analysis of sources of changes in the occupation composition of employment in Australia from the mid-1980s onwards, drawn from Ali et al. (2022). This analysis uses the ABS Longitudinal Labour Force Survey (LLFS). We track population flows between six states: employed in non-routine cognitive (NRC), routine cognitive (RC), non-routine manual (NRM) and routine manual (RM) occupations, unemployed (UE) and out of the labour force (OLF). This can be done on a quarterly basis using the LLFS, between February, May, August and November, for the rotation groups which can be matched across quarters.

Our method follows directly from Cortes et al. (2021): We use counter-factual analysis to estimate how the occupation composition of employment has been affected by changes over time in flows to and from the occupation groups. The basis of the counter-factual method is to estimate how changes in the proportions of the working-age population in each occupation group would have differed from the actual changes had flows between labour market states remained constant. This calculation is made separately for each occupation group and holding constant one flow at a time. For example, consider the routine manual occupation group. One counter-factual exercise estimates the change in the share of the population employed in that group had outflows from the group to non-routine cognitive occupations remained constant over the sample period. A second counter-factual estimates the change in the share of population employed in routine manual occupations had outflows to non-employment remained constant. And so on. Once the counter-factuals for all flows related to routine manual employment have been estimated, the exercise is repeated for the three other occupation groups. Comparing the counterfactual change in the population share of an occupation group to the actual change provides an estimate of the proportion of the change in its share that would have been avoided if the flow associated with that counter-factual remained constant.[30]

Table 2 presents results from decompositions constructed for the population aged 15-74 years.[31] Row (1) shows the 'actual' change in population share for each occupation group: from August 1986 to February 2020 (where the end value is calculated using the simulation method, allowing all flow rates to evolve over time according to their actual paths). Row (2) shows the counter-factual change in population shares for each occupation group if all flow rates were held constant at their average values over 1986-1989. Rows (3) to (8) show the fractions of the actual change in an occupation's population share that would have been avoided if no changes in inflow/outflow rates to/from UE or OLF or to/from the other occupation groups had occurred. In reporting

[30] For a formal description of the method, see the Appendix on 'Method for decomposing sources of changes in population shares of occupation groups'.

[31] In Ali et al. (2022) we show that changes in population shares of occupation groups constructed using simulation methods with the LLFS data closely track: (i) Changes in shares using stocks data from the LLFS; and (ii) Changes in shares using published LFS data.

the results for each occupation group we aggregate flows to/from UE and OLF into a single category of flows to/from non-employment; and we aggregate flows to/from the other three occupation groups into a single category of inter-occupation flows.

Table 2: Decomposition of sources of changes in population shares of occupation groups, 1986 to 2020

		NRC	RM	RC	NRM
1	'Actual' change in share (ppt)	+10.0	-4.3	-2.3	+4.5
2	Hypothetical change in share if no change in flow rates (ppt)	+1.3	+0.1	+1.4	+0.4
Fraction of change in share avoided if no change in flow rate (per cent)					
3	Inflow/Outflow rates – UE/OLF	24.5	16.1	20.9	50.0
4	Inflow rates – UE/OLF	17.2	31.3	50.0	22.8
5	Outflow rates – UE/OLF	7.5	-14.8	-29.3	28.3
6	Inflow/Outflow rates – Inter-occupation groups	60.7	68.8	120.0	38.9
7	Inflow rates – Inter-occupation	122.6	-53.9	-190.0	94.5
8	Outflow rates – Inter-occupation	-79.1	135.8	378.8	-75.1

Notes: Population aged 15 to 74, August 1986 to February 2020.
Source: Authors' calculations using ABS Longitudinal Labour Force Survey microdata.

A first finding is that changes in flow rates explain most of the changes in the occupation composition of employment from the mid to late 1980s to the present. This is evident from the hypothetical changes in the shares of the occupation groups had no changes in flow rates occurred being only a small fraction of the actual changes (comparing row (2) to row (1)).

A second finding is that changes in inter-occupation flows have been more important than flows to/from non-employment in determining changes in the occupation group shares. For NRC, RM and RC, flows to and from non-employment account for at most one-quarter of the change in the occupation group's share; although for NRM the fraction accounted for is one-half. Hence the decline in the share of routine occupations has been due mainly to the effects of faster outflows to other occupations dominating effects of faster inflows; and to a lesser extent to slower inflows from non-employment. The relative importance of inter-occupation flows and flows to/from non-employment is commensurate with the shares of population who are employed and not employed.

The decomposition analysis can be applied separately for different demographic groups (such as by gender or age category). This allows the different roles of those groups in explaining changes in the occupation group shares to be established. Analysis by gender, for example, establishes that the decreased share of routine manual employment has been due to mainly males having slower rates of inflow from non-employment and faster rates of outflow to other occupations; whereas the increased share of non-routine cognitive employment has happened primarily because females have had a slower rate of outflow to non-employment and a faster rate of inflow from other occupations.

4.iii.c] Changes in demand for labour by skill

The most common empirical approach to analyse the impact of new technologies on the demand for labour by skill uses highest level of education attainment as a proxy for skill. Changes in the relative demand for labour by level of education are inferred from data on labour supply and on earnings by education level together with assumptions on the 'production function' for aggregate output – and interpreted as representing the effect of technological change (Katz and Murphy, 1992; Acemoglu and Autor, 2011).

Consider an economy producing output using a CES production function with high and low-skill labour as inputs. Profit-maximisation implies a relation between the relative wages of high and low-skill workers (ω_t), the relative productivity of high and low-skill workers $\left(A_{H,t}/A_{L,t}\right)$ and the ratio of economy-wide supplies of high and low-skill labour (H_t/L_t):

$$\ln \omega_t = \frac{\sigma-1}{\sigma} \ln\left(\frac{A_{H,t}}{A_{L,t}}\right) - \frac{1}{\sigma} \ln\left(\frac{H_t}{L_t}\right) \tag{1}$$

where σ is the elasticity of substitution between high and low-skill labour.

An estimated path of the relative productivity of labour by skill level can be 'backed out' from equation (1), by applying estimates of the relative wages and supplies of high and low-skill labour and an assumption on the elasticity of substitution. This path is interpreted as a proxy for the impact of technological change on the relative productivity of workers by skill level.

We apply this empirical method to derive a series for the relative productivity of high-skill and low-skill labour in Australia. To do this we construct measures of relative wages and labour supplies by skill (level of education) using micro-data samples from the 5-yearly Australian Censuses from 1981 to 2016. For the wage ratio, high-skill is defined as employees with a Bachelors' degree and low-skill as employees with no post-school education (PSE). The wage ratio holds constant the age and gender composition of employees over the sample period. To calculate relative skill supplies, other categories of education are converted into 'efficiency units' of Bachelors' degree and no PSE (based on average wage rates relative to these two groups over the 1981 to 2016 period). For example, employed individuals with postgraduate degrees are part of the high-skill group with weights generally above one (average of 1.1 over age groups). Employed individuals with diplomas and certificates are split between the two groups.[32]

The Bachelors' degree to no PSE log wage ratio for Australia is depicted in Figure 4a. The ratio declined modestly from 1981 to 2001, then fell more quickly up to 2016. The relative supply of labour with a Bachelors' degree compared to no PSE is shown in Figure 4b. There is a strong upward trend in this series as the higher education sector in Australia expanded, although the rate of increase slows after 1996.

Figure 4a: Bachelors' degree to no PSE log wage gap, 1981 to 2016

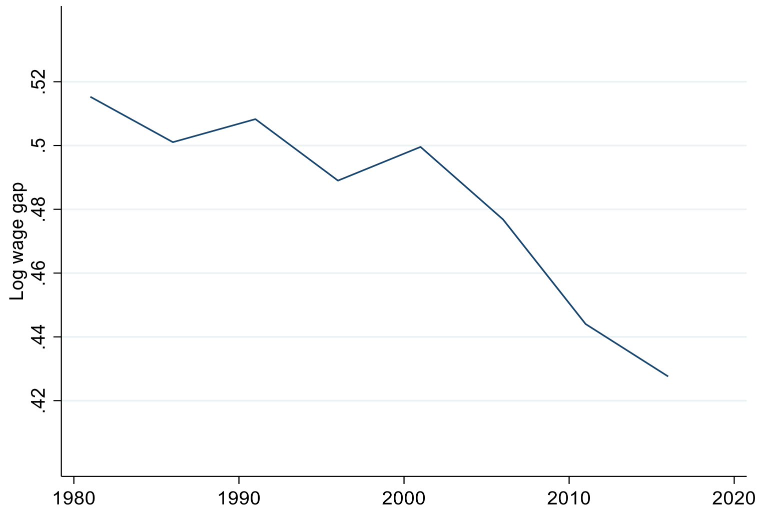
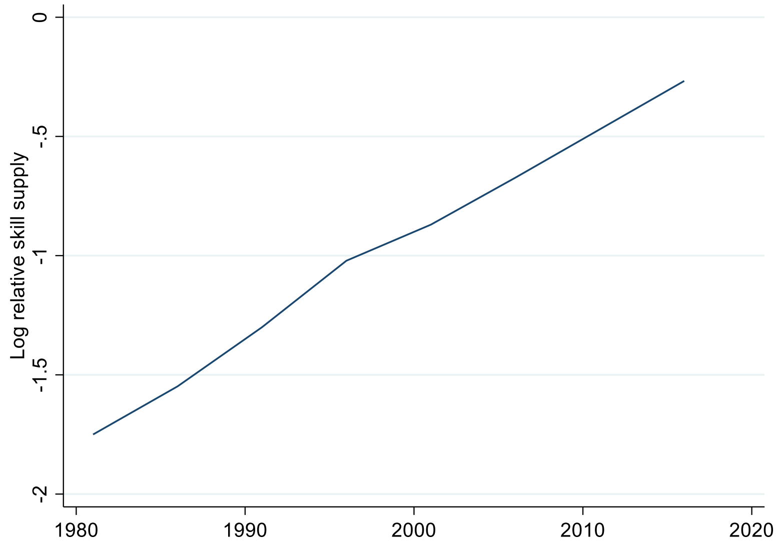


Figure 4b: Bachelors' degree to no PSE log relative skill supply, 1981 to 2016



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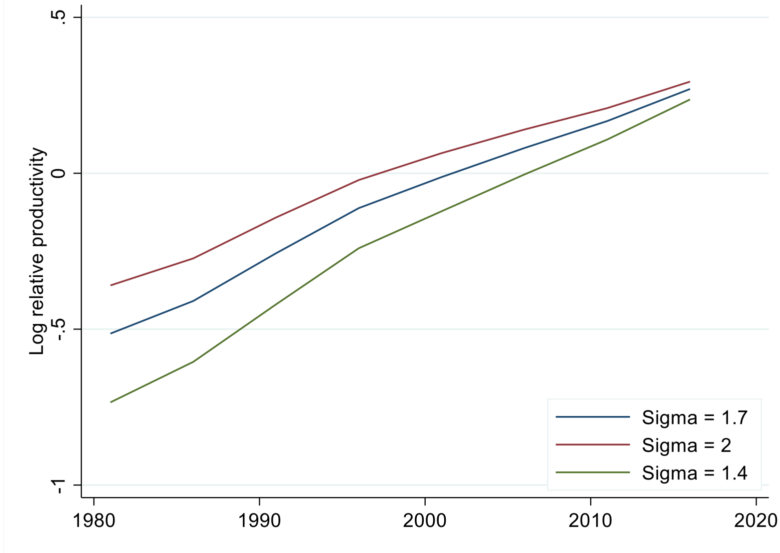
32 Diploma holders are split 55 per cent high skill and 45 per cent low skill on average. Certificate holders are split 15 per cent high skill and 85 per cent low skill on average.

The implied impact of technological change on the relative productivity of high-skill versus low-skill labour is shown in Figure 4c. Following Autor (2017) we assume that the elasticity of substitution is between 1.4 and 2.0. For all three values of σ, a similar story emerges.

Figure 4c: Implied log relative productivity term, 1981 to 2016



Technological change does appear to be skill-biased, with an upward trend in the relative productivity of high-skill compared to low-skill labour across the whole sample period. However, the rate of increase slows after 1996. Using the middle value for the elasticity of substitution of 1.7, the annual growth is 2.7 per cent up to 1996, and 1.9 per cent after that time.

The slowdown in the rate of increase in productivity of high-skill relative to low-skill labour explains why, even though growth in relative supply slows after the mid-1990s, relative wages of high-skill to low-skill workers decrease from the early 2000s onwards.

A similar slowdown in the rate of increase in relative productivity has been found for the United States. Autor (2017) estimates annual growth of 2.8 per cent for 1962 to 1992 and 1.8 per cent from 1992 to 2012 (using an elasticity of 1.6). Other studies for the United States have put the turning point at 2000 (Valletta, 2016; Beaudry et al., 2014).

The finding of a slow-down in the growth rate of relative productivity of high-skill to low-skill labour is puzzling, given the usual presumption that high-skill labour and digital technology are complements, and that technological change is ongoing. One possible explanation is that adoption of new digital technologies has slowed. Beaudry et al. (2014) suggest that maturation of the IT revolution, revealed in a large fall in investment in information processing equipment and software after 1999, was responsible for a slowdown in the trend of rising demand for highly educated labour in the United States. But Autor (2017) argues that the timing for this explanation is wrong, since the slow-down in relative demand happens in the United States in the early 1990s. For Australia also this explanation does not seem to fit the evidence on investment in IT equipment and software – with growth in investment in computer equipment and software taking off in the mid-1990s, just at the time we estimate the slow-down in the growth rate of relative productivities happened (see Figure 1). Perhaps an explanation may be related to what is happening to the productivity of low-skill workers rather than high-skill workers. Changes in the composition of tasks undertaken by low-skill labour or adoption of new types of capital equipment for performing those tasks might have caused the productivity of those workers to accelerate – but this is only speculation.

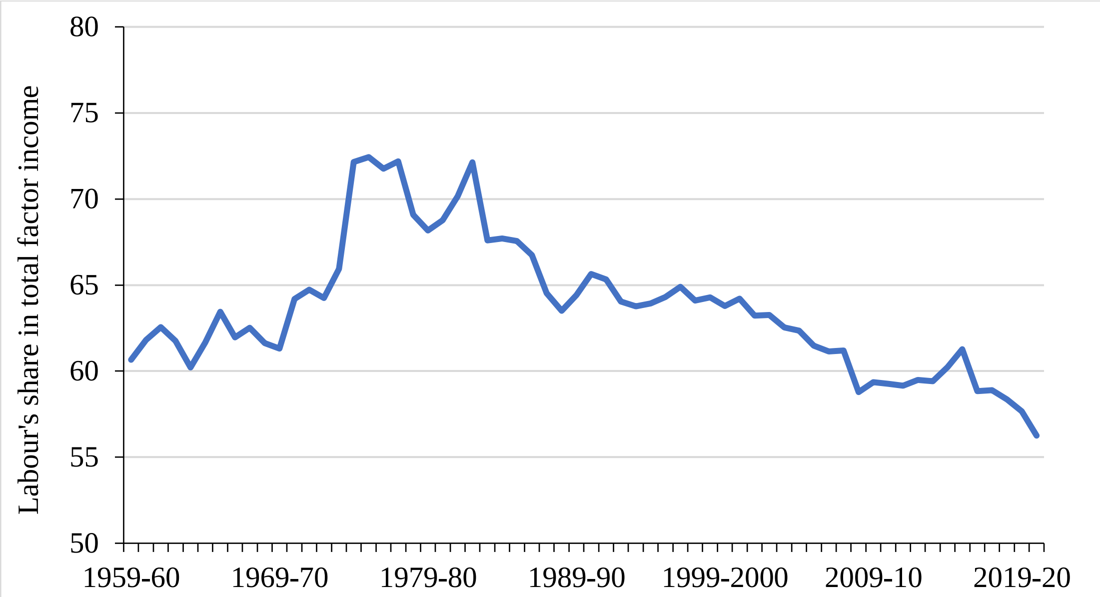
4.iv] Labour share

Changes in the demand for labour due to digital technologies can affect both employment and wages. Through either or both of those channels labour's share of income can then be affected. Recent theoretical studies have suggested a variety of reasons to expect that effect to be negative. A direct negative effect occurs where technology displaces labour or is capital augmenting, or technical progress lowers the price of capital and hence causes capital-labour substitution (for example, Summers, 2013; Acemoglu and Restrepo, 2019). Or the negative effect can be indirect, such as when a new technology increases an employer's degree of monopoly or monopsony power (for example, Autor, Dorn et al., 2020).

Figure 5 presents the labour share of income in Australia, from the 1960s to the present. In the early 1970s there was a rapid increase in the labour share due to the wage explosion in the period of the Whitlam government. That increase was then unwound in the following decade. From the mid-1980s to mid-1990s the labour share was relatively stable. Since the mid-1990s a steady decline in the labour share has occurred. This has attracted attention as potentially being due to the impact of new technologies.[33]

[33] The finding of a decrease in labour share from the mid-1990s is robust to alternative definitions of the labour share – such as excluding imputed rental income from the capital share, restricting attention to the corporate sector, making the capital share net of depreciation or holding constant the adjustment for self-employment at its value in 1996-97. See Trott and Vance (2018) and La Cava (2019) for further analysis.

Figure 5: Labour share of income, 1959-60 to 2020-21, Australia



Notes: Labour share = Compensation of employees*Ratio of (employees plus self-employed) to employees/Total factor income.

Sources: Data on labour income and total factor income from ABS, Australian System of National Accounts, Table 46; Labour income adjusted by ratio of (employees + self-employed)/employees: 1] 1959-60 to 1981-82: Classification of wage and salary earners, self-employed and employers – Norton et al., Australian Economic Statistics: 1949-50 to 1980-81 I: Tables, Table 4.7 (1959-60 to 1963-64: Annual average; 1964-65 to 1981-82: August); 2] 1982-83 to 1990-91 (August): Classification of employee, employer and own account workers - ABS, Labour Force Australia, Detailed – Electronic Delivery, catalogue no.6291.0.55.001, Table 08; 3] 1991-92 to 2019-20 (12 month average): Classification of employees and owner managers of incorporated enterprises ABS, Labour Force Australia - Detailed, Table 08. (See Cowgill, 2013, Appendix A).

The sources of the decline in the labour share of income after 1996-97 can be decomposed between the effects of changes in: (i) average hourly wages; (ii) hourly labour productivity; and (iii) the ratio of output prices to consumer prices. This is represented formally as:

$$\begin{aligned} \%\Delta\, \textit{Labour share} = &\ \%\Delta\, \textit{Real (CPI adjusted) hourly compensation} \\ &- \%\Delta\, \textit{Labour productivity (per hour worked)} \\ &- \%\Delta\, (\textit{Output price})/(\textit{Consumer price}) \qquad (2) \end{aligned}$$

The results from a decomposition of changes in the labour share based on equation (2) are reported in Table 3. Several distinct phases are evident. In the first phase, from 1996-97 to 2003-04, the decrease in labour share was explained by real hourly compensation growing at a slower rate than labour productivity. In the second phase, during the mining boom from 2003-04 to 2011-12, real hourly compensation grew at a faster rate than labour productivity. But that positive effect on labour share was more than offset by a negative effect due to an increase in the ratio of output prices to consumer prices. In the most recent phase, from 2011-12 onwards, the decrease in labour share has again been due to real hourly compensation growing at a slower rate than labour productivity.[34]

Table 3: Sources of decrease in the labour share of income, decomposition analysis, 1996-97 to 2020-21, Australia

	Annual change in:			
	Real hourly compensation (CPI adjusted)	Labour productivity (per hour worked)	Output price/CPI	Total change
1996-97 to 2003-04	1.62	2.30	-0.14	-0.56
2003-04 to 2011-12	1.84	1.28	1.25	-0.69
2011-12 to 2020-21	0.51	1.45	-0.38	-0.56

Note: In the calculation of labour productivity per hour, real GDP is adjusted by the ratio of current GDP to total factor income. This adjustment means that the decomposition is exact.

Sources: Compensation ‑ ABS, System of National Accounts, Table 46; CPI ‑ ABS, Consumer Price Index Australia, Table 1; GDP (Real and current) ‑ ABS, System of National Accounts, Table 1; Annual hours worked ‑ ABS, Labour Force Australia, Table 19; Output price deflator ‑ Calculated as ratio of current to real GDP.

International research that has investigated the effect of digital technologies on the labour share emphasises the industry dimension, in particular the role of manufacturing and retail industries. For example, for the United States, Hubmer and Restrepo (2021, p.3) conclude that: '…capital-labor substitution played a key role in explaining the decline in the manufacturing labor share; whereas rising competition and reallocation towards firms with lower labor shares played a key role in retail and other sectors.'

However, for Australia the industry pattern of changes in the labour share has been quite different. Table 4 presents findings from a shift-share analysis of the effect of between and within-industry changes on the overall labour share in Australia for the period from 1996-97 to 2020-21. It is decreases in the labour shares in mining, construction, finance and insurance and professional, scientific and technical services that mainly account for the decline in the overall share. Changes in the labour share in retail had a small negative effect on the overall share, whereas changes in manufacturing had a positive effect. The manufacturing effect reflects that the labour share increased within a majority of 2-digit manufacturing industries.

Of course, it is still possible that it is the application of digital technologies that accounts for the decrease in labour share within industries that explain the decline in overall

[34] Andrews et al. (2019) report findings from a firm-level analysis of the relation between wages and productivity growth in Australia from the start of the 2000s.

share in Australia. For example, both mining and finance have seen major investment in technologies to automate tasks over the past two decades (Heath, 2019; La Cava, 2019).

Table 4: Sources of decrease in labour share of income, industry shift-share analysis, 1996-97 to 2020-21, Australia

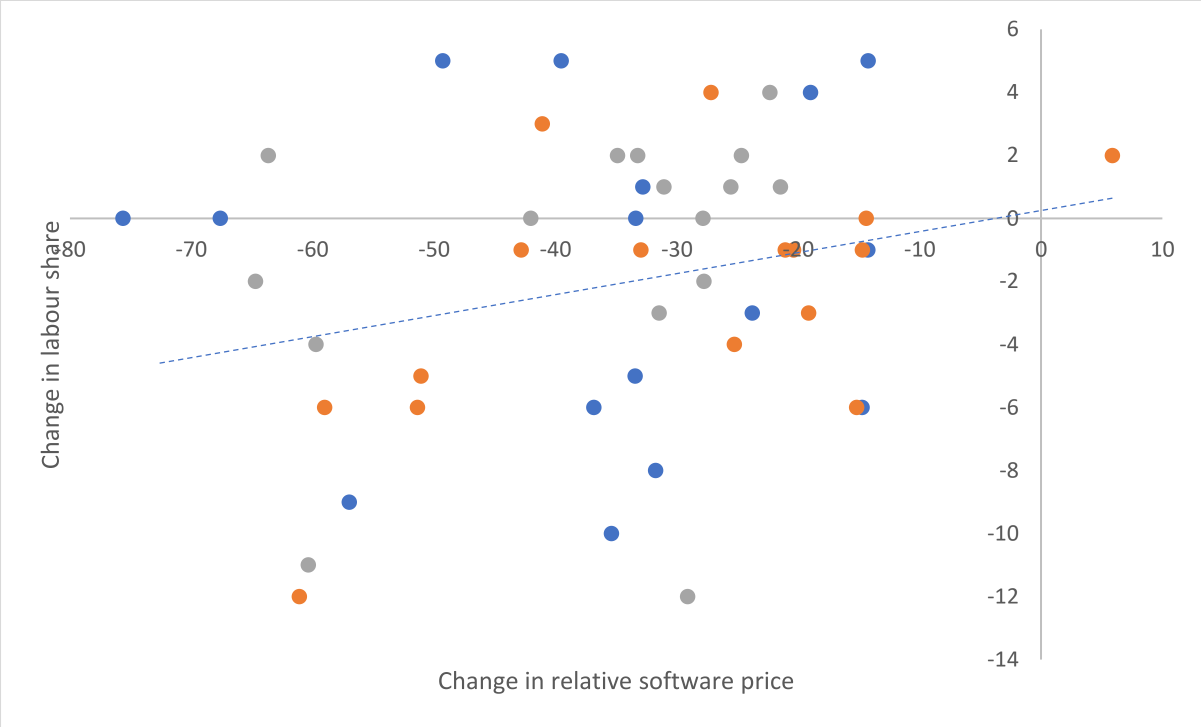
	1996-97 to 2020-21	Ave(1994-95 to 1998-99) to Ave(2016-17 to 2020-21)
Total change	-7.62	-5.26
i] Change in composition of factor income	-0.94	-0.92
ii] Changes in share of labour income for selected industries:		
Mining	-1.80	-1.31
Construction	-0.95	-0.70
Finance and insurance services	-0.71	-0.87
Professional, scientific and technical services	-0.87	-0.69
Manufacturing	+0.37	+0.67
Retail trade	-0.74	-0.29

Sources: Labour shares by industry: ABS, Estimates of Multifactor Productivity, Table 14; Factor income by industry: Table 46.

As a next step, the impact of digital technologies on the labour share can be assessed by looking at correlations between industry-level changes in the labour share and various proxies for the impact of digital technologies. Updating earlier analysis by La Cava (2019) we use three proxies: (i) changes in software prices; (ii) changes in the share of employment in routine jobs; and (iii) changes in product market concentration. It is important to note that these correlations provide only a partial equilibrium perspective; and ignore general equilibrium adjustments such as changes in factor prices or in the relative supply of labour by skill (Grossman and Oberfield, 2021, pp.7-9).

Industry-level changes in the labour share and the relative price of software are shown in Figure 6a, with each observation being at the industry level for one of the three sub-periods into which we have classified changes in the overall labour share. Software has accounted on average for 47.6% of IT spending since 1996-97.

Figure 6a: Correlation between changes in labour share and changes in relative software prices, by industry and time period, 1996-97 to 2019-20, Australia



Notes: 1] Industry groups = ANZSIC categories A, B, C, D, E, F, G, H, I, J, K, L, M, N, R and S.
2] Blue = 1997-97 to 2003-04; Grey = 2003-04 to 2011-12; Orange = 2011-12 to 2020-21
3] Relative software price = Implicit price deflator for software/Implicit price deflator for GVA. Industry-level implicit price for software/GVA is calculated as ratio of current price and chain-linked volume of software/GVA.

Sources: Industry-level labour shares: ABS, Estimates of Multifactor Productivity, Table 14; Relative software price: ABS, Australian System of National Accounts, Tables 5 and 70.

A positive association between industry-level changes in the labour share and relative software prices appears to exist, and the association is marginally statistically significant (p-value = 0.075). But there is no evidence of a faster rate of decrease in software prices post-1996-97.[35] As well, there are other reasons to be cautious before concluding that this provides evidence of an impact of technology – such as the possibility of correlation between the relative software price and other drivers of the labour share (Grossman and Oberfeld, 2021, pp.11-12).[36]

[35] See Appendix Figure 2.

[36] There is evidence of a faster rate of decrease in computer prices after 1996-97. But there are only minimal differences in the changes in computer prices between industries. Hence changes in computer prices do not seem to explain inter-industry differences in changes in labour shares. Computers and peripherals account for 24.5 per cent of IT spending over the whole period.

Industry-level changes in the labour share and changes in the routine share of employment are shown in Figure 6b. There is not much evidence of correlation. The same conclusion is drawn from analysis for 2-digit manufacturing industries.

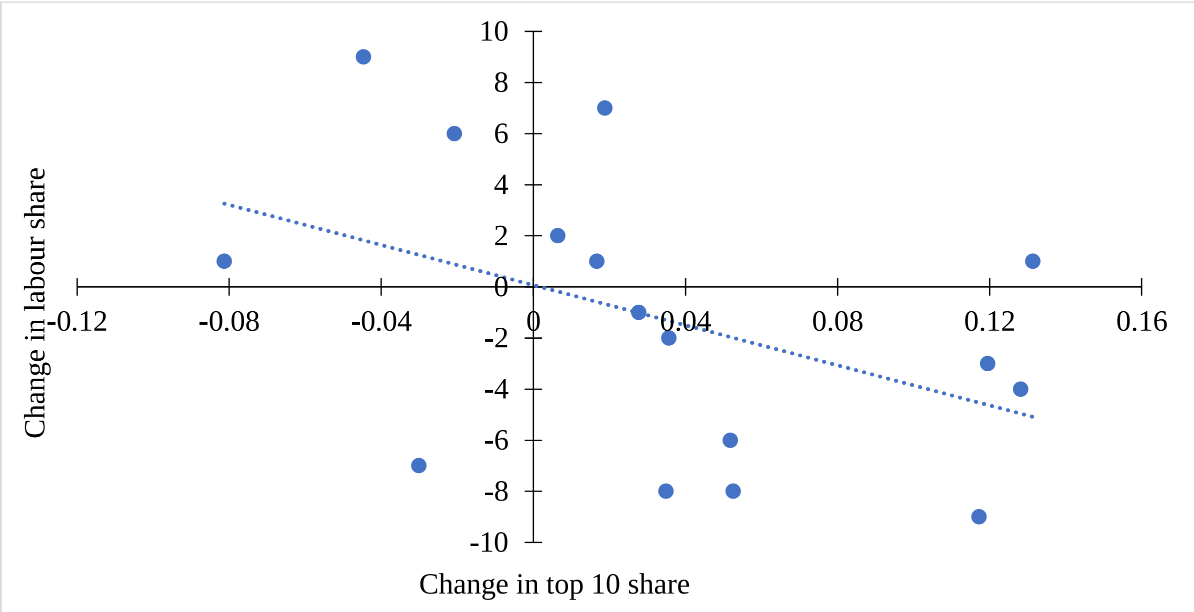
Figure 6b: Correlation between changes in labour share and changes in routine share of employment, by industry, 1990-91 to 2015-16, Australia

Note: Industry groups = ANZSIC industry categories: A, B, C, D, E, F/G, H, I, J, K/L, R and S.
Sources: Industry-level labour shares: ABS, Estimates of Multifactor Productivity, Table 14;
Routine employment share: ABS, Census of Population and Housing, Microdata files.

Finally, Figure 6c presents changes in the industry-level labour share and changes in the market share of the top 10 firms in each industry. A negative correlation is apparent, with the association being marginally statistically significant (p-value = 0.081). While this is suggestive, it must be kept in mind that there are other explanations apart from technological change for why market concentration has altered.[37]

[37] For further analysis of changes in market concentration in Australia, see Hambur (2021) and Hambur and La Cava (2018).

Figure 6c: Correlation between changes in labour share and changes in market share of output of top 10 firms, by industry, 2001-02 to 2014-15



Note: Industry groups = ANZSIC categories A, B, C, D, E, F, G, H, I, J, K, L, M, N, R and S.
Sources: Industry-level labour shares: ABS, Estimates of Multifactor Productivity, Table 14;
Change in market share of top 10 firms: La Cava (2019).

4.v] Summary

The increased adoption of digital technologies – which in Australia can be dated to the period beginning from the mid-1990s - does not appear to have caused any decline in the total amount of work available in Australia. Either that, or what would have been a negative impact of the technologies has been systematically offset by other factors.

What adoption of those (and other) new technologies has done is to decrease demand for workers who are trained to undertake routine tasks and increase demand for workers able to perform non-routine cognitive tasks. These trends in demand extend back as far as the mid-1960s and have been relatively steady across the whole of that time. That the declining demand for workers to perform routine tasks was underway well before the rise of digital technologies makes the point that adoption of those technologies is simply the most recent stage in a long-run process of automating routine tasks. [38]

The rising demand for workers to perform non-routine cognitive tasks has been associated with an increase in the relative demand for high-skill to low-skill labour.

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[38] Analysis by Squicciarini and Staccioli (2022) finds that the share of labour-saving patents in total patents has been relatively stable over time 'confirming that labour-saving goals behind technological innovation are not a new phenomenon, but rather a quite established one' (p.6).

This in turn caused an increase in demand for workers with higher levels of formal education, such as university qualifications. Since the early 1980s there has been a rapid expansion in the proportion of the Australian population with a Bachelors' degree (or higher) qualification.

The adoption of digital technologies also seems likely to have had consequences for the distribution of income. In Australia there has been a relatively large decline in the labour share of income since the mid-1990s, which matches with the timing of take-up of digital technologies. Industries which have accounted for the decline in the overall labour share in Australia are finance, mining, construction, professional services and to some extent retail trade. While this industry pattern in Australia differs from other countries, it does not necessarily rule out digital technologies having been important in explaining the decrease in the labour share. For example, decreases in labour shares in finance and mining may be in part due to the introduction of new technologies in those industries. Industry-level analysis finds correlation between changes in labour share and variables proxying for the impact of technology: changes in software prices and market concentration. However, there are reasons for being cautious about drawing conclusions from these correlations.[39]

Underlying the changes in the occupation composition of employment that have occurred due to adoption of new technologies has been a dynamic process of adjustment. Understanding that adjustment process is likely to be important for policy. For example, our preliminary analysis suggests a major contributor to the decreased share of routine manual employment has been from males having a slower rate of inflow to those jobs from non-employment.

5] Has COVID-19 accelerated the impact of the digital economy?

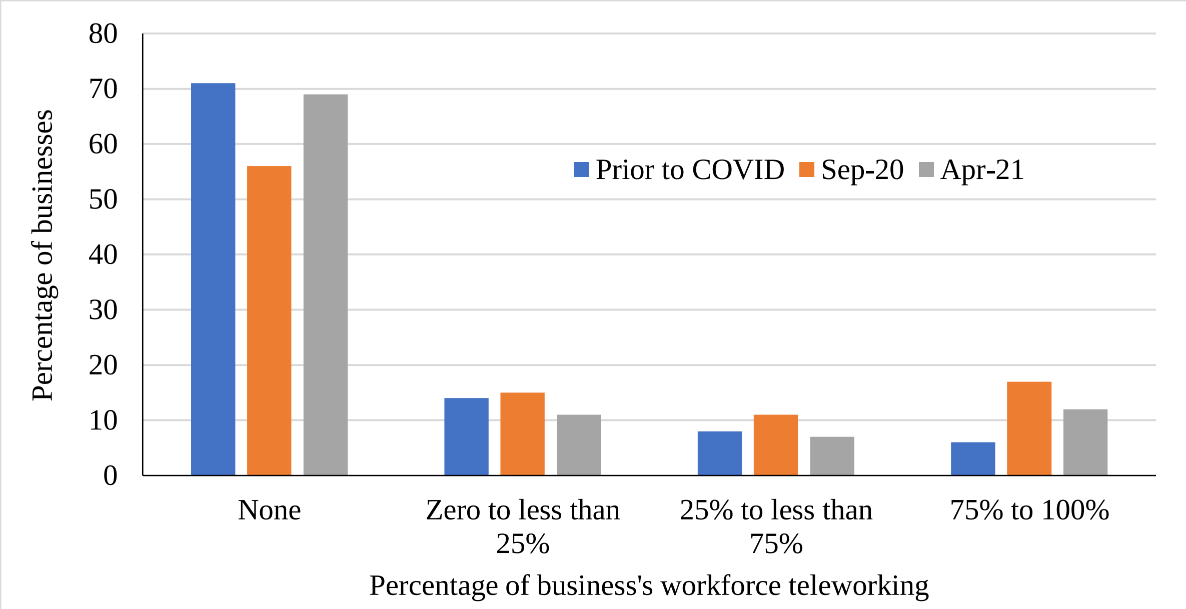
Notable aspects of the impact of COVID-19, such as the shift to working from home and increased use of online retail methods, may have temporarily accelerated the application of digital technologies. As well, labour shortages during the pandemic may have made it profitable for businesses to adopt labour-replacing technologies that otherwise they would not have done (or not until a later time).

The incidence of working from home has increased substantially during the pandemic. Persons who regularly work from home, whose share of employment had grown slowly from 29.8 per cent to 32.2 per cent between 2015 and 2019, accounted for 40.6 per cent

[39] Other analysis for Australia has suggested that globalisation or institutional factors may be an important explanation for the decline in labour share in Australia – see Isaac (2018) and La Cava (2019).

of employment in 2021 (ABS, 2021).[40] In the same vein, data reported in Figure 7 show that the proportion of businesses with an arrangement for some staff to telework rose from 29 per cent prior to COVID-19 to 44 per cent in September 2020.

Figure 7: Incidence of telework, prior to and during the pandemic, Australia

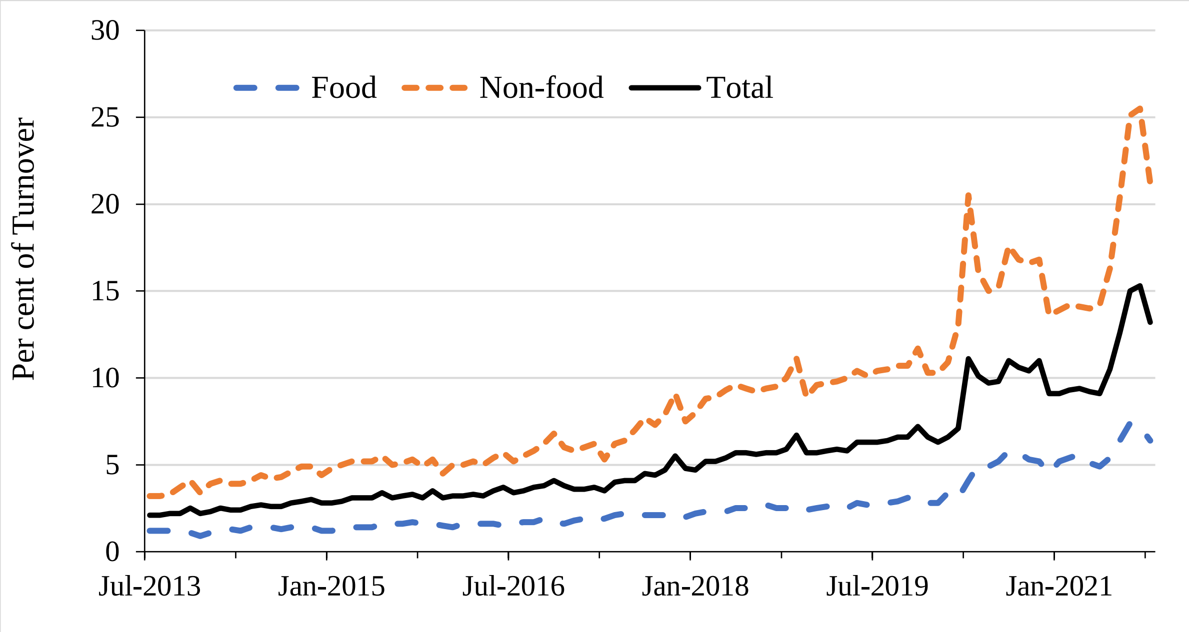


Source: ABS, Business Conditions and Sentiments, September 2020 and April 2021.

COVID-19 has also brought a step-up in the use of online selling. Figure 8 shows the share of retail activity occurring online in Australia from the early 2010s. From mid-2013 to early 2020 the share had grown steadily from 2 per cent to 6.5 per cent. With the onset of the pandemic, online selling rose to be 10 per cent of retail turnover during 2020. As COVID-19 was brought under control in Australia in early 2021, the share fell, but only back to 9 per cent, about 1.5 per cent above where its previous trend would have taken it. And as COVID-19 re-emerged in NSW and Victoria from mid-2021, the share increased to 15 per cent.

[40] The increase from 2019 to 2021 was due to increased proportions of employed persons answering that they had flexible working arrangements (6.2 per cent to 9.0 per cent) or were working at home for other reasons (3.0 per cent to 11.4 per cent) – ABS, Characteristics of Employment, 2021 – Tablebuilder.

Figure 8: Online retail sales as a share of total retail turnover, July 2013 to October 2021, Australia



Source: ABS, Retail Trade, Australia, Table 23.

There are several reasons why these shifts may not be fully undone with the end of the pandemic (Productivity Commission, 2021; Barrero et al., 2020, 2021). First, COVID-19 can be interpreted as an episode of 'forced learning'. Organisations and workers have learnt about the benefits and costs of alternative production methods such as working from home and substituting virtual meetings for travel. Similarly, retailers and consumers have learnt more about online selling and distribution methods. This learning may cause permanent adjustments in behaviour – that for example, could bring a step change in the incidence of working from home and online buying. The learning behind these changes may have needed to be forced due to market failure in experimentation – perhaps because of public good problems associated with information acquisition or the role of habit in behaviour. Second, organisations may have accelerated irreversible automation during the pandemic as they sought to shift to production methods with lower costs or that are more resilient to the pandemic (such as selling online). Third, the increased use of digital technologies during the pandemic likely increased the payoff to investment to improve those technologies (such as tools for virtual meetings), hence making their permanent adoption more likely.

6] Policy implications

Policies directed to the labour market impacts of digital technologies should have two main objectives: first, to facilitate the optimal level of adoption of the new technologies to maximise average living standards; and second, to address adjustment and distributional consequences that arise with adoption of the technologies, as well as potential conflicts with other policy goals.

Technological change is the only *long-term* basis for productivity growth; and hence for growth in average real wages and material living standards (Productivity Commission, 2020). In general, therefore, it should be encouraged. In the labour market, this involves ensuring that the workforce has appropriate skills to apply the new technologies; and preventing what might be unwarranted barriers to the implementation of new technologies.

Having a workforce with appropriate skills to apply new technologies requires an education and training system that allows students to acquire relevant skills; and scope for workers to reskill during their work careers. Achieving this general policy objective is a task of considerable complexity. Knowing what skills for working with digital technologies are needed is made difficult by those skills varying so much between jobs (from being able to use a laptop through to writing new software programs) and because forecasting future demand for jobs is never straightforward. Even if the demand for digital skills can be charted, sufficient numbers of students must be attracted into the education and training programs. Ensuring that the programs are designed to provide career-ready graduates is a further challenge.

To some extent, the training of local workers with skills to work with digital technologies may be substituted for by migration to Australia of workers with necessary skills. Immigration can be a useful way of dealing with short-term shortages of labour with required skills; but there can also be a danger that supply of labour via immigration then becomes 'locked-in', acting as a disincentive to training of the local workforce.

A major potential source of barriers to implementation of new technologies is labour market regulations. One example is where occupational licensing delays or prevents the adoption of new best-practice production methods (for example, Bambalaite et al., 2020). Another example is the impact of job security rules. A recent study for Europe finds that unwinding of employment protection in the early 2000s caused firms to redirect innovation away from implementing labour-saving technologies towards product development (Manera and Uccioli, 2021).

Using policy to achieve the optimal level of adoption of digital technologies may also involve ensuring that there is not over-adoption relative to the optimum. Recent commentary on this issue has focused on how taxation policy may create a bias in production towards using capital relative to labour; so that the level of automation is greater than socially optimal (Acemoglu, Manera and Restrepo, 2020).

Displacement of workers by new technologies creates a twofold policy problem. First, policy is needed to facilitate the adjustment and re-employment of workers who lose their jobs due to technological change. The disparate nature of technology-based layoffs (for example, by region and type of worker) has made this a difficult problem. But as well, an unwillingness to commit sufficient resources is likely to have mattered. The United States Trade Adjustment Assistance program provides a model for how a more intensive adjustment program can have positive impacts (Hyman, 2018). Second, there should be an adequate safety net for those who are temporarily or permanently disadvantaged by job loss due to new technologies. In this regard, debate about the adequacy of existing income support payments in Australia, such as JobSeeker, are relevant (for example, Australian Council of Social Service, 2020). Others go further and suggest that technological unemployment is a reason for giving serious consideration to a universal basic income scheme (for example, Garnaut, 2021, chapter 8).

New digital technologies also present issues relating to the distribution of earnings among workers. At the top of the distribution, the rise in the share of earnings accruing to the top one per cent has been attributed (amongst other causes) to technology-based superstar effects. At the bottom of the distribution, digital technology has allowed the development of labour markets (such as platform-based markets) outside existing regulatory structures with minimum standards for wages and working conditions. What is happening at the top of the distribution seems an issue for tax policy. What is happening at the bottom of the distribution may require regulation to bring new labour markets into the domain of existing regulations or specific interventions for those markets.[41]

The impact of new digital technologies also needs to be monitored to ensure that other labour market-related policy goals are not being compromised. An example is the use of AI in hiring. To the uninitiated the application of AI may seem a neutral way to judge talent. But AI is being driven by a human-designed algorithm which can embed discriminatory preferences, and often in a more hidden way (Broad, 2018, chapter 9).

In addition, AI algorithms may yield discriminatory outcomes even without biases being driven by algorithm designers. AI may lead to statistical discrimination whereby the algorithm may base outcomes on simple correlates of demographic groups. For

[41] As an example, Mas and Pallais (2020, p.653) propose that a minimum wage for rideshare drivers could be achieved by requiring platforms to specify shifts over which drivers would be guaranteed a minimum income provided they accepted all rides offered in that time or that the platforms be required to achieve minimum utilisation rates for drivers over specified time intervals.

example, the algorithm may base predictions on where people live rather than directly on race, but the two are often highly correlated (Duenez-Guzman et al., 2021).

7] Lessons

To conclude, we discuss some general lessons about understanding the impact of technology on labour market outcomes:

1] The history of technological change throws up many recurring patterns and themes. But that does not mean the implications of future technological change will remain the same forever. Take the example of the types of workers affected by technological change. These days we are used to thinking that the impact of technological change is to cause low or middle-skill labour to be replaced with capital. However, historical analyses suggest that during the nineteenth century the impact was for high-skill labour to be replaced by a combination of machines and low-skill labour (Katz and Margo, 2014, p.16). That is, a long-run perspective shows that the types of workers whose jobs become redundant due to technological change can evolve over time. The general point is that we need always to have regard for uncertainty about the impact of new technologies. That uncertainty means that the best way to think about the future is in terms of possible scenarios, with some sense of what the probabilities of those scenarios might be; and to allow the scenarios and probabilities to evolve as we learn during each episode of technological change.

2] Technological change can affect labour market outcomes in many ways. Focusing attention on the ways most likely to be policy-relevant is important. In the late 2010s a great amount of effort was devoted to considering whether digital technologies might be causing the end of work. In our view, at that time such a debate was unproductive, and should have been quickly dismissed. Instead, it would have been much better to spend more time thinking about a known constant associated with the adoption of new technologies, the displacement effect; and considering which workers would be likely to be displaced by digital technologies in coming years and how they might be assisted. As Herbert Simon wrote 50 years ago (1966; and cited in Autor, 2015, p.28): 'The bogeyman of automation consumes worrying capacity that should be saved for real problems…'.

3] Technological change is only one of several main drivers of labour market outcomes. It is important therefore to maintain a balanced approach to thinking about its influence on the future of work; and to give due consideration to other drivers such as globalisation, demographics (for example, ageing population and increased female participation) and institutional and policy settings (for example, institutions for wage-setting and immigration policies).

4] Policy is an important mediating influence on how new technologies affect the labour market and society. To remain relevant and effective, policy needs to adapt to technological change. But that reform can afford to be gradual. This is because, while there are phases of faster and slower technological change, those phases tend to be long-lasting, and within the phases changes in labour market outcomes are evolutionary, not revolutionary. An example is the continuous steady change in the proportions of workers doing routine and non-routine jobs in Australia in the past 50 years.

References

Abraham, Katharine, John Haltiwanger, Kristin Sandusky and James Speltzer (2019), 'The rise of the gig economy: Fact or fiction', *AEA Papers and Proceedings*, 109: 357-61.

Acemoglu, Daron (2002), 'Technical change, inequality and the labor market', *Journal of Economic Literature*, 40(1): 7-72.

Acemoglu, Daron (2021), 'Harms of AI', National Bureau of Economic Research, Working Paper no. 29247.

Acemoglu, Daron and David Autor (2011), 'Skills, tasks and technologies: Implications for employment and earnings', *Handbook of Labor Economics Volume 4b* (Elsevier): 1044-1171.

Acemoglu, Daron, Claire Lelarge and Pascual Restrepo (2020), 'Competing with robots: Firm-level evidence from France', *AEA Papers and Proceedings*, 110: 383-88.

Acemoglu, Daron, Andrea Manera and Pascual Restrepo (2020), 'Does the US tax code favor automation?' *Brookings Papers on Economic Activity*, Spring: 231-300.

Acemoglu, Daron and Pascual Restrepo (2018), 'The race between man and machine: Implications of technology for growth, factor shares and employment', *American Economic Review*, 108(6): 1488-1542.

Acemoglu, Daron and Pascual Restrepo (2019), 'Automation and new tasks: How technology displaces and reinstates labor', *Journal of Economic Perspectives*, 33(2): 3-30.

Acemoglu, Daron and Pascual Restrepo (2020a), 'Unpacking skill bias: Automation and new tasks', *AEA Papers and Proceedings*, 110: 356-61.

Acemoglu, Daron and Pascual Restrepo (2020b), 'Robots and jobs: Evidence from US labor markets', *Journal of Political Economy*, 128(6): 2188-2244.

Acemoglu, Daron and Pascual Restrepo (2021), 'Tasks, automation and the rise in US wage inequality', National Bureau of Economic Research, Working Paper no. 28920.

Acemoglu, Daron and Pascual Restrepo (2022), 'Demographics and automation', *Review of Economic Studies*, 89(1): 1-44.

Adachi, Daisuke, Daiji Kawaguchi and Yukiko Umeno Saito (2020), 'Robots and employment: Evidence from Japan, 1978-2017', RIETI Discussion Paper Series 20-E-051.

Adams, Abi (2018), 'Technology and the labour market: the assessment', *Oxford Review of Economic Policy*, 34(3): 349-61.

Agrawal, Ajay, Joshua Gans and Avi Goldfarb (2019), 'Artificial Intelligence: The ambiguous labor market impact of automating prediction', *Journal of Economic Perspectives*, 33(2): 31-50.

Alexander, Oliver, Jeff Borland, Andrew Charlton and Amit Singh (2022), 'The labour market for Uber drivers in Australia', *Australian Economic Review*, forthcoming.

Ali, Abuzar, Jeff Borland and Michael Coelli (2022), 'Disappearing routine and rising non-routine jobs: the role of occupational dynamics', mimeo.

Allen, Robert (2009), *The British Industrial Revolution in Global Perspective* (Cambridge University Press: Cambridge).

Allen, Robert (2018), 'The hand-loom weaver and the power-loom: A Schumpeterian perspective', *European Review of Economic History*, 22(4): 381-402.

Altindag, Duha, Elif Filiz and Erdal Tekin (2021), 'In online education working?' National Bureau of Economic Research, Working Paper no. 29113.

Andrews, Dan, Nathan Deutcher, Jonathan Hambur and David Hansell (2019), 'Wage growth in Australia: Lessons from longitudinal microdata', Treasury Working Paper 2019-04.

Andrews, Dan and David Hansell (2019), 'Productivity-enhancing labour reallocation in Australia', Treasury Working Paper 2019-06.

Atack, Jeremy, Robert Margo and Paul Rhode (2019), '"Automation" of manufacturing in the late nineteenth century: the Hand and Machine Labor Study', *Journal of Economic Perspectives*, 33(2): 51-70.

Atalay, Enghin, Phai Phongthiengtham, Sebastian Sotelo and Daniel Tannenbaum (2020), 'The evolution of work in the United States', *American Economic Journal: Applied Economics*, 12(2): 1-34.

Australian Bureau of Statistics (2021), 'Media release: More than 40 per cent of Australians worked from home'. Accessed at: https://www.abs.gov.au/media-centre/media-releases/more-40-cent-australians-worked-home

Australian Council of Social Service (2020), 'Raise the rate of Newstart and other allowances', mimeo. Accessed at: https://www.acoss.org.au/wp-content/uploads/2020/01/200229-Newstart-Increase-Briefing-Note.pdf

Autor, David (2013), 'The "task approach" to labor markets: an overview', *Journal of Labour Market Research*, 46: 185-99.

Autor, David (2015), 'Why are there still so many jobs? The history and future of workplace automation', *Journal of Economic Perspectives*, 29(3): 3-30.

Autor, David (2017), 'How long has this been going on? A discussion of "Recent flattening in the higher education wage premium: polarization, skill downgrading, or both?" by Robert G. Valletta', mimeo. Accessed at: https://economics.mit.edu/files/12563

Autor, David and David Dorn (2013), 'The growth of low-skill service jobs and the polarization of the US labor market', *American Economic Review*, 103(5): 1553-97.

Autor, David, David Dorn, Lawrence Katz, Christina Patterson and John Van Reenen (2020), 'The fall of the labor share and the rise of superstar firms', *Quarterly Journal of Economics*, 135(2): 645-709.

Autor, David, Claudia Goldin and Lawrence Katz (2020), 'Extending the race between education and technology', *AEA Papers and Proceedings*, 110: 347-51.

Autor, David, Frank Levy and Richard Murnane (2002), 'Upstairs, downstairs: Computers and skills on two floors of a large bank', *Industrial and Labor Relations Review*, 55(3): 432-447.

Autor, David, Frank Levy and Richard Murnane (2003), 'The skill content of recent technological change: an empirical exploration', *Quarterly Journal of Economics*, 118(4): 1279-1333.

Autor, David and Anna Salomons (2018), 'Is automation labor-share displacing? Productivity growth, employment and the labor share', *Brookings Papers on Economic Activity*, Spring: 1-87.

Autor, David, Anna Salomons and Bryan Seegmiller (2021), 'New frontiers: The origins and content of new work, 1940-2018', mimeo. Accessed at: https://economics.mit.edu/files/21810

Bambalaite, Indre, Giuseppe Nicoletti and Christina von Rueden (2020), 'Occupational entry regulations and their effects on productivity in services: firm-level evidence', OECD Economics Department Working Papers, no. 1605. Accessed at: https://www.oecd-ilibrary.org/economics/occupational-entry-regulations-and-their-effects-on-productivity-in-services-firm-level-evidence_c8b88d8b-en

Barrero, Jose Maria, Nicholas Bloom and Steven J. Davis (2020), 'COVID-19 is also a reallocation shock', *Brookings Papers on Economic Activity*, Summer: 329-71.

Barrero, Jose Maria, Nicholas Bloom and Steven J. Davis (2021), 'Why working from home will stick', National Bureau of Economic Research, Working Paper no. 28731.

Bartel, Ann, Casey Ichniowski and Kathryn Shaw (2007), 'How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement and worker skills', *Quarterly Journal of Economics*, 122(4): 1721-58.

Baumol, William (1967), 'Macroeconomics of unbalanced growth: The anatomy of urban crisis', *American Economic Review*, 57(3): 415-26.

Beaudry, Paul, David A. Green and Benjamin Sand (2014), 'The Declining Fortunes of the Young Since 2000', *American Economic Review*, 104(5): 381–86.

Berg, Janine and Hannah Johnston (2019), 'Too good to be true? A comment on Hall and Krueger's analysis of the labor market for Uber's driver-partners', *Industrial and Labor Relations Review*, 72(1): 39-68.

Berger, Thor, Carl Benedikt Frey, Guy Levin and Santosh Rao Danda (2019), 'Uber happy? Work and well-being in the 'Gig Economy'', *Economic Policy*, 34(99): 429-77.

Berger, Thor, Chinchi Chen and Carl Benedikt Frey (2018), 'Drivers of disruption? Estimating the Uber effect', *European Economic Review*, 110: 197-210.

Bessen, James, Maarten Goos, Anna Salomons and Wiljan van den Berge (2019), 'Automatic reaction – what happens to workers at firms that automate?' Boston University School of Law, Law & Economics Working Paper No. 19-2.

Bessen, James, Maarten Goos, Anna Salomons and Wiljan van den Berge (2020), 'Firm-level automation: Evidence from the Netherlands', *AEA Papers and Proceedings*, 110: 389-93.

Bishop, James and Iris Chan (2019), 'Is declining union membership contributing to low wages growth?' RBA Discussion Paper 2019-02.

Blanas, Sotiris, Gino Gancia and Sang Yoon Lee (2019), 'Who is afraid of machines?' *Economic Policy*, 34(100): 627-90.

Bloom, Nicholas, James Liang, John Roberts and Zichun Jenny Ying (2015), 'Does working from home work? Evidence from a Chinese experiment', *Quarterly Journal of Economics*, 130(1): 165-218.

Bonfiglioli, Alessandra, Rosario Crino, Harald Fadinger and Gino Gancia (2020), 'Robot imports and firm-level outcomes', CESifo Working Paper no. 8741.

Borland, Jeff and Michael Coelli (2017), 'Are robots taking our jobs?' *Australian Economic Review*, 50(4): 377-97.

Bound, John and George Johnson (1992), 'Changes in the structure of wages in the 1980s: An evaluation of alternative explanations', *American Economic Review*, 82(3): 371-92.

Bracha, Anat and Mary Burke (2021), 'How big is the gig? The extensive margin, the intensive margin, and the hidden margin', *Labour Economics*, 69, article 101974.

Bresnahan, Timothy, Erik Brynjolfsson and Lorin Hitt (2002), 'Information technology, workplace organization and the demand for skilled labor: Firm-level evidence', *Quarterly Journal of Economics*, 117(1): 339-76.

Broad, Ellen (2018), *Made by Humans: The AI Condition* (Melbourne University Press: Melbourne).

Cheng, Hong, Ruixue Jia, Dandan Li and Hongbin Li (2019), 'The rise of robots in China', *Journal of Economic Perspectives*, 33(2): 71-88.

Chiacchio, Francesco, Georgios Petropoulos and David Pichler (2018), 'The impact of industrial robots on EU employment and wages: A local labour market approach', Bruegel, Working paper issue 2.

Coelli, Michael and Jeff Borland (2016), 'Job polarisation and earnings inequality in Australia', *Economic Record*, 92(296): 1-27.

Coelli, Michael and Jeff Borland (2019), 'Behind the headline number: Why not to rely on Frey and Osborne's predictions of potential job loss from automation', Melbourne Institute of Applied Social and Economic Research, University of Melbourne, Working Paper no. 10/19.

Collins, Brett, Andrew Garin, Emilie Jackson, Dmitri Koustas and Mark Payne (2019), 'Is gig work replacing traditional employment? Evidence from two decades of tax returns', mimeo. Accessed at:
https://www.irs.gov/pub/irs-soi/19rpgigworkreplacingtraditionalemployment.pdf

Comin, Diego, Ana Danieli and Marti Mestieri (2020), 'Income-driven labor market polarization', National Bureau of Economic Research, Working Paper no. 27455.

Cortes, Guido, Nir Jaimovich, Christopher Nekarda and Henry Siu (2021), 'The dynamics of disappearing routine jobs: A flows approach', *Labour Economics*, 69, Article 101823.

Cowgill, Matthew (2013), 'A shrinking slice of the pie', ACTU Working Paper no.1. Accessed at:
https://www.actu.org.au/media/297315/Shrinking%20Slice%20of%20the%20Pie%202013%20Final.pdf

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum and Nicole Woessner (2021), 'The adjustment of labour markets to robots', *Journal of the European Economic Association*, 19(6): 3104-53.

David, Paul (1979), *Technical Choice, Innovation and Economic Growth: Essays on American and British Experience in the Nineteenth Century* (Cambridge University Press: Cambridge).

De Loecker, Jan, Jan Eeckhout and Simon Mongey (2021), 'Quantifying market power and business dynamism in the macroeconomy', National Bureau of Economic Research, Working Paper no. 28761.

de Vries, Gaaitzen, Elisabetta Gentile, Sebastien Miroudot and Konstantin Wacker (2020), 'The rise of robots and the fall of routine jobs', *Labour Economics*, 66, Article 101885.

Deming, David and Kadeem Noray (2020), 'Earnings dynamics, changing job skills, and STEM careers', *Quarterly Journal of Economics*, 135(4): 1965-2005.

Deming, David (2021), 'The growing importance of decision-making on the job', National Bureau of Economic Research, Working Paper no. 28733.

Duéñez-Guzmán, Edgar A., Kevin R. McKee, Yiran Mao, Ben Coppin, Silvia Chiappa, Alexander Sasha Vezhnevets, Michiel A. Bakker, Yoram Bachrach, Suzanne Sadedin, William Isaac, Karl Tuyls and Joel Z. Leibo, (2021) 'Statistical discrimination in learning agents,' mimeo. Accessed at: https://arxiv.org/pdf/2110.11404.pdf

Dixon, Jay, Bryan Hong and Lynn Wu (2020), 'The employment consequences of robots – Firm-level evidence', Statistics Canada, mimeo. Accessed at: https://content.lesaffaires.com/LAF/lacom2019/robots.pdf

Dvorkin, Maximiliano and Alexander Monge-Naranjo (2019), 'Occupation mobility, human capital and the aggregate consequences of task-biased innovations', Federal Reserve Bank of St. Louis, Working Paper 2019-013C.

Eggleston, Karen, Yong Suk Lee and Toshiaki Iizuka (2021), 'Robots and labor in the service sector: Evidence from nursing homes', National Bureau of Economic Research, Working Paper no. 28322.

Escueta, Maya, Vincent Quan, Andre Nickow and Philip Oreopoulos (2017), 'Education technology: An evidence-based review', National Bureau of Economic Research, Working Paper no. 23744.

Faber, Marius (2020), 'Robots and reshoring: Evidence from Mexican labor markets', *Journal of International Economics*, 127, article 103384.

Farrell, Diana, Fiona Greig and Amar Hamoudi (2019a), 'The evolution of the online platform economy: Evidence from five years of banking data', *AEA Papers and Proceedings*, 109: 362-66.

Farrell, Diana, Fiona Greig and Amar Hamoudi (2019b), *The Online Platform Economy in 2018: Drivers, Workers, Sellers, and Lessors*, JP Morgan Chase. Accessed at: https://www.jpmorganchase.com/corporate/institute/document/institute-ope-2018.pdf

Feigenbaum, James and Daniel Gross (2020), 'Automation and the future of young workers: Evidence from telephone operation in the early 20th century', National Bureau of Economic Research, Working Paper no. 28061.

Freeman, Richard (2002), 'The labour market in the new information economy', National Bureau of Economic Research, Working Paper no. 9254.

Freeman, Richard, Ina Ganguli and Michael Handel (2020), 'Within-occupation changes dominate changes in what workers do: A shift-share decomposition, 2005-2015', *AEA Papers and Proceedings*, 110: 394-99.

Frey, Carl Benedikt and Michael Osborne (2017), 'The future of employment: How susceptible are jobs to computerisation?' *Technological Forecasting and Social Change*, 114: 254-80.

Futterman, Matthew (2016), *Players: The Story of Sports and Money, and the Visionaries Who Fought to Create a Revolution* (Simon and Schuster: New York).

Garnaut, Ross (2021), *Reset: Restoring Australia After the Pandemic Recession* (Latrobe University Press: Carlton).

Goos, Maarten (2018), 'The impact of technological progress on labour markets: policy challenges', *Oxford Review of Economic Policy*, 34(3): 362-75.

Goos, Maarten, Alan Manning and Anna Salomons (2009), 'Job polarization in Europe', *AEA Papers and Proceedings*, 99(2): 58-63.

Graetz, Georg and Guy Michaels (2018), 'Robots at work', *Review of Economics and Statistics*, 100(5): 753-68.

Green, David A. and Benjamin Sand (2015), 'Has the Canadian labour market polarized?' *Canadian Journal of Economics*, 48(2): 612-46.

Grennan, Jillian and Roni Michaely (2020), 'Artificial intelligence and high-skilled work: Evidence from analysts', Swiss Finance Institute, Research paper Series no. 20-84.

Griliches, Zvi (1969), 'Capital-skill complementarity', *Review of Economics and Statistics*, 51(4): 465-68.

Grossman, Gene and Ezra Oberfield (2021), 'The elusive explanation for the declining labor share', National Bureau of Economic Research, Working Paper no. 29165.

Hall, Jonathan and Alan Krueger (2018), 'An analysis of the labor market for Uber's driver-partners in the United States', *Industrial and Labor Relations Review*, 71(3): 705-32.

Hall, Jonathan and Alan Krueger (2019), 'Reply to the comment by Berg and Johnston', *Industrial and Labor Relations Review*, 72(1): 69-74.

Hambur, Jonathan (2021), 'Product market power and its implications for the Australian economy', Treasury Working Paper 2021-03.

Hambur, Jonathan and Gianni La Cava (2018), 'Business concentration and mark-ups in the retail trade sector', *RBA Bulletin*, December: 1-24.

Heath, Alex (2019), 'Australia's resource industry – A look into the crystal ball', Address to the Association of Mining and Exploration Companies, June 5. Accessed at: https://www.rba.gov.au/speeches/2019/sp-so-2019-06-05.html

Heath, Alex (2020), 'Skills, technology and the future of work', Address to the Career Education Association of Victoria and Victorian Commercial Teachers Association Work Futures Conference. Accessed at: https://www.rba.gov.au/speeches/2020/sp-so-2020-03-16.html

Hubmer, Joachim and Pascual Restrepo (2021), 'Not a typical firm: The joint dynamics of firms, labour share and capital-labor substitution', National Bureau of Economic Research, Working Paper no. 28579.

Humlum, Anders (2019), 'Robot adoption and labor market dynamics', mimeo. Accessed at: https://economics.yale.edu/sites/default/files/humlumjmp_111419.pdf

Hyman, Louis, Erica Groshen, Adam Seth Litwin, Martin Wells, Kwelina Thompson and Kyrylo Chernyshov (2020), 'Platform driving in Seattle', Institute for Workplace Studies, ILR School, Cornell University. Accessed at: https://static1.squarespace.com/static/5acbd8e736099b27ba4cfb36/t/60b41137c81f1253bd09e91c/1622413626875/Hyman_TAA_Nov2018.pdf

Isaac, Joe (2018), 'Why are Australian wages lagging and what can be done about it?' *Australian Economic Review*, 51(2): 175-90.

Jackson, Emilie (2019), 'Availability of the gig economy and long run labor supply effects for the unemployed', mimeo. Accessed at:

https://economics.nd.edu/assets/348621/jackson_jmp.pdf

Jacoby, Sanford M. (2021), *Labor in the Age of Finance: Pensions, Politics, and Corporations from Deindustrialization to Dodd-Frank* (UK, Princeton University Press).

Katz, Lawrence and Alan Krueger (2019), 'The rise and nature of alternative work arrangements in the United States, 1995-2015', *Industrial and Labor Relations Review*, 72(2): 382-416.

Katz, Lawrence and Robert Margo (2014), 'Technical change and the relative demand for skilled labor: The United States in historical perspective' pp. 15-57 in Leah Boustan, Carola Frydman and Robert Margo (eds.) *Human Capital in History: The American Record* (University of Chicago Press: Chicago).

Katz, Lawrence and Kevin M. Murphy (1992), 'Changes in relative wages, 1963-1987: Supply and demand factors', *Quarterly Journal of Economics*, 107(1): 35-78.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru and Matt Tady (2021), 'Measuring technological innovation over the long-run', *American Economic Review: Insights*, 3(3): 303-20.

Koch, Michael, Ilya Manuylov and Marcel Smolka (2019), 'Robots and firms', CESifo Working Paper no. 7608, Center for Economic Studies and ifo Institute, Munich.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence Schmidt and Bryan Seegmiller (2021), 'Technology-skill complementarity and labor displacement: Evidence from linking two centuries of patents with occupations', National Bureau of Economic Research, Working Paper no. 29552.

Koustas, Dmitri (2019), 'What do big data tell us about why people take gig economy jobs?' *AEA Papers and Proceedings*, 109: 367-71.

Krenz, Astrid, Klaus Pettner and Holger Strulik (2018), 'Robots, reshoring and the lot of low-skilled workers', Center for European, Goverenance and Economic Development Research, Discussion Paper no. 351, University of Gottingen.

Krussell, Per, Lee Ohanian, Jose-Victor Rios-Rull and Giovanni Violante (2000), 'Capital-skill complementarity and inequality: A macroeconomic analysis', *Econometrica*, 68(5): 1029-53.

Kuhn, Peter (2014), 'The internet as a labor market matchmaker', *IZA World of Labor*, 18 doi: 10.15185/izawol.18.

Kuhn, Peter and Hani Mansour (2014), 'Is internet job search still ineffective?' *Economic Journal*, 124(581): 1213-33.

La Cava, Gianni (2019), 'The labour and capital shares of income in Australia', *RBA Bulletin*, March: 1-22.

Landier, Augustin, Daniel Szomoru and David Thesmar (2016), 'Working in the on-demand economy; An analysis of Uber driver-partners in France', mimeo. Accessed at: https://turinschool.eu/files/turinschool/Landier_Uber_drivers.pdf.

Lass, Inga and Mark Wooden (2020), 'Trends in the prevalence of non-standard employment in Australia', *Journal of Industrial Relations*, 62(1): 3-32.

Levin, Jonathan (2011), 'The economics of internet markets', National Bureau of Economic Research, Working Paper no. 16852.

Mandelman, Federico and Andrei Zlate (2022), 'Offshoring, automation, low-skilled immigration, and labor market polarization', *American Economic Journal: Macroeconomics*, 14(1): 355-89.

Manera, Andrea and Martina Uccioli (2021), 'Employment protection and the direction of technology adoption', mimeo. Accessed at: http://economics.mit.edu/files/22059

Mas, Alexandre and Amanda Pallais (2017), 'Valuing alternative work arrangements', *American Economic Review*, 107(12): 3722-59.

Mas, Alexandre and Amanda Pallais (2020), 'Alternative work arrangements', *Annual Review of Economics*, 12(1): 631-58.

McDonald, Paula, Penny Williams, Andrew Stewart, Robyn Mayes and Damian Olivier (2019), 'Digital platform work in Australia: Prevalence, nature and impact', Report commissioned by Victorian Department of Premier and Cabinet. Accessed at: https://s3.ap-southeast-2.amazonaws.com/hdp.au.prod.app.vic-engage.files/7315/9254/1260/Digital_Platform_Work_in_Australia_-_Prevalence_Nature_and_Impact_-_November_2019.pdf

Mokyr, Joel, Chris Vickers and Nicholas Ziebarth (2015), 'The history of technological anxiety and the future of economic growth: Is this time different?' *Journal of Economic Perspectives*, 29(3): 31-50.

Productivity Commission (2020), *PC Productivity Insights: Australia's Long-term Productivity Experience*, no. 3, Canberra.

Productivity Commission (2021), *Working From Home*, Research Paper, Canberra.

Rizk, Nagla (2017), 'A glimpse into the sharing economy: An analysis of Uber partner-drivers in Egypt', mimeo; accessed at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2946083.

Rosen, Sherwin (1981), 'The Economics of Superstars', *American Economic Review* 71(5): 845–58.

Simon, Herbert (1966), 'Automation', *New York Review of Books*, May 26.

Squicciarini, Mariagrazia and Jacopo Staccioli (2022), 'Labour-saving technologies and employment levels: Are robots really making workers redundant?', OECD Science, Technology and Industry Policy Papers, No. 124.

Stansbury, Anna and Lawrence Summers (2020), 'The declining worker power hypothesis: An explanation for the recent evolution of the American economy', National Bureau of Economic Research, Working Paper no. 27193.

Summers, Lawrence (2013), 'Economic possibilities for our children', *NBER Reporter 4*, December. Accessed at: https://www.nber.org/reporter/2013number4/economic-possibilities-our-children

Szymanski, Stefan (2015), *Money and Soccer: A soccernomics guide* (Nation Books: New York).

Trott, Declan and Leo Vance (2018), 'Adjusting the Australian labour share for depreciation, housing and other factors', *Economic Papers*, 37(4): 412-28.

Valletta, Robert (2016), 'Recent flattening in the higher education wage premium: polarization, skill downgrading, or both?' National Bureau of Economic Research, Working Paper no. 22935.

Webb, Michael (2020), 'The impact of Artificial Intelligence on the labor market', mimeo. Accessed at: http://i8.hexun.com/2019-12-25/199788177.pdf

Yuen, Kelvin and Patrick Cumming (2021), 'Labour market transitions of workers during COVID-19', Fair Work Commission, Research Report 2021/2.

Appendix Table 1: Studies of industrial robots

Study	Country/Time period	How effect of robots identified	Main findings
1] Industry-level			
Graetz and Michaels (2018)	17 OECD countries; 1993-2007; Data on robot intensity from International Federation of Robotics	Impact of variation between industries in exposure to robots on labour productivity and employment. Exposure to robots measured by robot density at country/industry-level (IV: (i)Fraction of each industry's hours worked in occupations that subsequently became replaceable by robots; and (ii) Extent to which an industry's occupations relied on reaching and handling tasks.)	1] Increase in robot density over sample period increased labour productivity by 0.36 per cent pa; and 2] No effect on employment – but shift in composition of employment away from low-skill labour.
Chiacchio et al. (2018)	Finland, France, Germany, Italy, Spain, Sweden; 1995-2007; Data on robot intensity from International Federation of Robotics	Impact of variation in exposure to industrial robots between commuting zones on employment and wages. Variation in exposure to robots between commuting zones predicted via differences in industry composition of employment and industry-level intensity of robot usage. (IV: Similar measure for other countries in Europe; Rigidity of labour market institutions)	1] One extra robot per 1,000 workers causes 0.16-0.2 per cent decrease in employment and no significant effect on wages; and 2] Largest negative effect on employment of young and middle-skill workers.
Acemoglu and Restrepo (2020b)	United States; 1990-2007; Data on robot intensity from	Impact of variation in exposure to industrial robots between commuting zones on employment and wages. Variation in exposure to robots	1] One extra robot per 1,000 workers causes 0.2 per cent decrease in employment and 0.42 percent decrease in wages; and

	International Federation of Robotics	between commuting zones predicted via differences in industry composition of employment and industry-level intensity of robot usage. (IV: Similar measure for Europe)	2] Negative employment effects concentrated on routine manual occupations in heavily-robotized manufacturing industries.
Adachi et al. (2020)	Japan; 1978-2017; Data from Japan Robot Association on shipments, applications etc. of robots	1] Impact of variation in stock of robots by industry on employment; 2] Impact of exposure to robots by commuting zone (IV: Price of robots; Where variation derives from industry-level variation in robot applications and changes over time in relative prices of applications)	1] Industry-level: 1 per cent increase in use of robots causes 0.28 per cent increase in employment; and 2] Commuting zone: One extra robot per 1,000 workers causes increase of 2.2 per cent in employment, 1.9 per cent decrease in hours per worker and 4.1 per cent increase in hourly wage.
Dauth et al. (2021)	Germany; 1994-2014; Data on robot intensity from International Federation of Robotics	Impact of variation in exposure to industrial robots between commuting zones on employment and wages. Variation in exposure to robots between commuting zones predicted via differences in industry composition of employment and industry-level intensity of robot usage. (IV: Similar measure for Europe)	1] Zero effect on total employment; 2] Negative impact on manufacturing employment (displacement) offset by positive effect on non-manufacturing employment (reallocation) (primarily business services); 3] Displacement effect largest for workers in routine occupations; and 4] Increased adoption of robots within a firm raises likelihood of worker retention (in new jobs at higher skill level; and most likely to occur where employment protection is higher), but for dismissed workers make it more difficult to regain employment. Main adjustment to adoption of robots is via decreased inflow of young workers (but offset by increased inflow to services).
Dvorkin and Monge-Naranjo (2019)	United States; 1990-2007; Data	Impact of variation in exposure to industrial robots between commuting	Negative effect on employment concentrated on routine manual occupations.

	on robot intensity from International Federation of Robotics	zones on employment. Variation in exposure to robots between commuting zones predicted via differences in industry composition of employment and industry-level intensity of robot usage. (IV: Similar measure for Europe.) Also controls for number of personal computers per employee.	
Blanas et al. (2019)	10 developed economies; 1996-2005; Data on robot intensity from International Federation of Robotics	Impact of variation in exposure to industrial robots between countries on industry-level employment. Variation in exposure to robots is predicted based on source countries from which each country buys robots and expansion over time in sales of robots by those source countries.	1] Increase in exposure to robots causes decrease (increase) in employment and income share of low skill (medium and high skill) workers; 2] Displacement effect on low-skill workers concentrated in manufacturing. Positive effects for medium and high-skill workers in both manufacturing and services.
Krenz et al. (2018)	48 developed countries x 9 manufacturing industries; 2000-14; Data on robot intensity from International Federation of Robotics	Impact of variation in exposure to industrial robots between countries on industry-level employment. Variation in exposure to robots is based on actual usage of robots.	1] Increase of 1 robot per 1,000 workers is associated with a 3.5 per cent increase in reshoring activity; and 2] Reshoring is positively associated with wages and employment for high-skill labour, but not low-skill labour.
De Vries et al. (2020)	37 countries x 19 industries; 2005-15; Data on robot	Impact of variation between industries in exposure to robots on labour productivity and employment. Exposure to robots measured by robot	1] No significant relation between robot adoption and employment growth; and 2] Increased use of robots associated with increase in share of employment accounted for

	intensity from International Federation of Robotics	density at country/industry-level (IV: (i)Fraction of each industry's hours worked in occupations that subsequently became replaceable by robots; and (ii) Extent to which an industry's occupations relied on reaching and handling tasks.)	by analytic non-routine jobs and decrease in share accounted for by routine manual jobs.
2] Firm-level			
Koch et al. (2019)	Spain; 1990-2016; Manufacturing; Data from panel firm-level survey: Encuesta Sobre Estrategias Empresariales	Panel model: (i) Impact of firm-level robot adoption (0/1) on output, employment etc; (ii) Impact of market-level robot adoption on non-adopting firms	1] Firms in the top quartile of productivity/output have the highest probability of adopting robots; Exporting is associated with a higher likelihood of adopting robots; 2] Adoption of robots increases output by 25 per cent within 4 years; 3] Adoption of robots increases employment by 10 per cent, decreases labour cost share by 7 per cent and has no effect on average wages; 4] A non-adopting firm loses 10 per cent of sales when market share of robot-adopting firms increases from zero to 50 per cent; and 5] Robot adoption accounts for one-third of TFP growth over sample period – About two-third due to within-firm effect and one-third due to reallocation effect
Humlum (2019)	Denmark; 1995-2015; Data on shipments of robots from Danish Foreign Trade Statistics	1] Difference-in-difference analysis of impact of robot adoption at firm-level on sales and employment; and 2] General equilibrium: Estimation of equilibrium effects on wages and welfare from robot adoption	1] Difference-in-difference: Robot adoption event associated with 20 per cent increase in sales and 8 per cent increase in wage bill. Demand for production workers decreases by 20 per cent and for tech workers increases by 30 per cent;

	Register + Statistics Denmark firm-level survey on robot adoption	experienced in Denmark from 1995-2015.	2] GE: Industrial robots have increased average real wages by 0.8 per cent. Average real wages are 6 per cent lower for production workers and 2.3 per cent higher for tech workers. Welfare losses concentrated on older workers who are less mobile between occupations.
Acemoglu, Lelarge and Restrepo (2020)	France; 2010-15; Manufacturing: Robot data from Ministry of Industry survey	1] Direct effect: Impact of whether a firm ever adopted robots between 2010-15 on employment, labour productivity etc; and 2] Spillovers: Impact of incidence of adopting robots by competitors.	1] 20 percentage point increase in robot adoption causes 3.2 per cent decrease in industry-level employment; and 2] Firm-level impact of increased robots is to increase employment and labour productivity and to decrease labour share and share of production workers in employment – Negative industry-level impact is explained by negative spillovers from firms adopting robots to non-adopters; and faster growth potential of adopters.
Bonfiglioli et al. (2020)	France; 1994-2013; Robot data (imports by firm) from French Customs Authority	Impact on employment etc of firm-level variation (over time) in: 1] Robot intensity (stock or robot imports/stock of capital); and 2] Initial average robot intensity within detailed industry in which firm is competing interacted with share of workers at a firm doing tasks that can be replaced with robots.	1] Robots adopted by firms where employment had been growing. But after robot adoption employment decreases. Share of low-skill workers decreases; 2] Estimated effect on total firm-level employment is sensitive to properly controlling for firm-level demand changes – ie., need to avoid spurious positive correlation between robotization and employment due to positive relationship of both variables with demand.
Bessen et al. (2019)	Netherlands; 2000-16;	Event study of impact of firm-level 'automation event' on employment and	1] Workers lose on average 8.2 per cent of wage income in five years after an automation

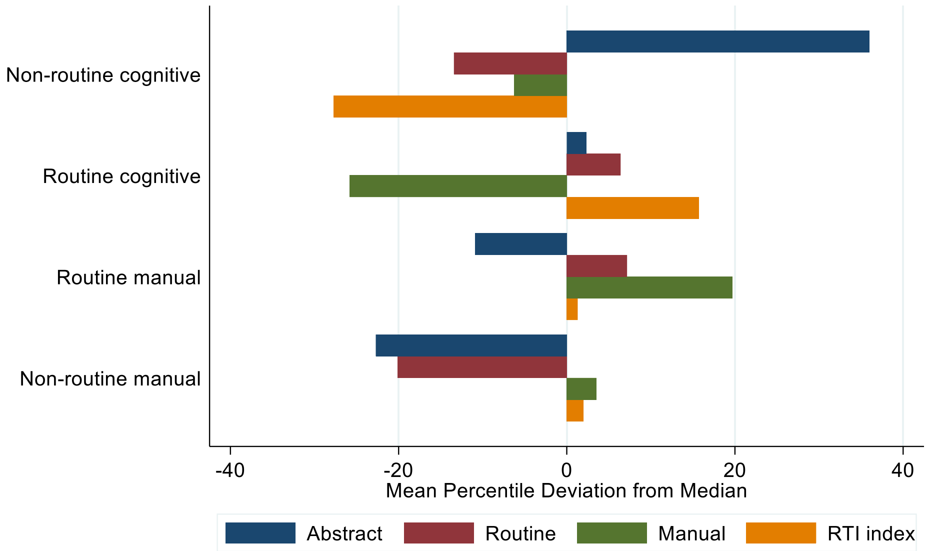
	Statistics Netherlands – Production Statistics: All nonfinancial private sector firms with more than 50 employees - Variable for automation costs	wages. (Automation event = Single year spike in spending on automation at least 3 times average spending on automation).	event (cf. usual growth of 1.6 per cent per year). Income loss is larger for incumbent workers than recent hires; 2] Workers at firms with an automation event are 24 per cent more likely to separate. Increase in separation probability for both incumbents and recent hires – but average time out of employment is then larger for incumbents than recent hires; and 3] Older and higher-wage workers more adversely affected.
Bessen et al. (2020)	Netherlands; 2000-16; Statistics Netherlands – Production Statistics: All nonfinancial private sector firms with more than 50 employees - Variable for automation costs	Impact of firm-level 'automation event' on employment and wages. (Automation event = Single year spike in spending on automation at least 3 times average spending on automation). Study: (i) Effect of at least one automation event between 2000-16; and (ii) Event study of impacts prior to and after an automation event.	1] At least one automation event between 2000-16 increases employment by 1.8 to 2 per cent per annum. But event study shows decrease in employment following automation event; and 2] No effect on wages from automation event between 2000-16. But event study shows decreases in wages following an automation event.
Dixon et al. (2020)	Canada; 2000-15; Canadian Border Services – Purchases of robots by Canadian firms	Impact of variation in firm-level robot capital stock on employment etc.	1] Higher robot capital stock predicts higher employment – Decrease in managerial employment and increase in non-managerial employment; 2] Higher robot capital stock associated with higher turnover of managerial and non-managerial employees;

			3] Take-up of robots mainly motivated by desire to improve product quality/services; and 4] Mixed effect on centralisation of authority in organisation.
Eggleston et al. (2021)	Japan; 2017; Nursing homes; Data from Care Work Foundation Survey on robot adoption + Administrative information on subsidies provided for purchases of robots	Impact of home-level variation in adoption of robots for long-term care on employment and wages (IV: Average planned adoption of robots per home by prefecture)	1] Robot adopting homes have 28 per cent extra care workers and 39 per cent extra nurses than non-adopting homes. Impact is entirely from extra non-regular workers; 2] Robot adopting homes have lower average monthly wages, especially for nurses (about 22 per cent); 3] Labour share decreases by 7 per cent; and 4] Effects mainly driven by monitoring robots and aid robots.

Appendix Table 2: Classifying 4-digit ANZSCO occupations into Figure 2 categories

Figure 2a category	Figure 2b category	ANZSCO codes
Non-routine cognitive	Managers	1000-1499
	Professionals	2000-2726
	Technicians	3000-3132, 3993, 3995
Routine manual	Production	3200-3424, 3600-3900, 3920-3992, 3994, 3996, 3999, 5612
	Operators/Labourers	5612, 7000-8000, 8210-8419, 8900-8990, 8992-8995, 8999
Routine cognitive	Office/Administration	5000-5611, 5613-5999
	Sales	6000-6399, 8997
Non-routine manual	Protective service	4400-4422, 8991
	Food/ Cleaning	3510-3514, 4310-4319, 8110-8116, 8510-8513, 8996
	Personal care	4000-4234, 4500-4524

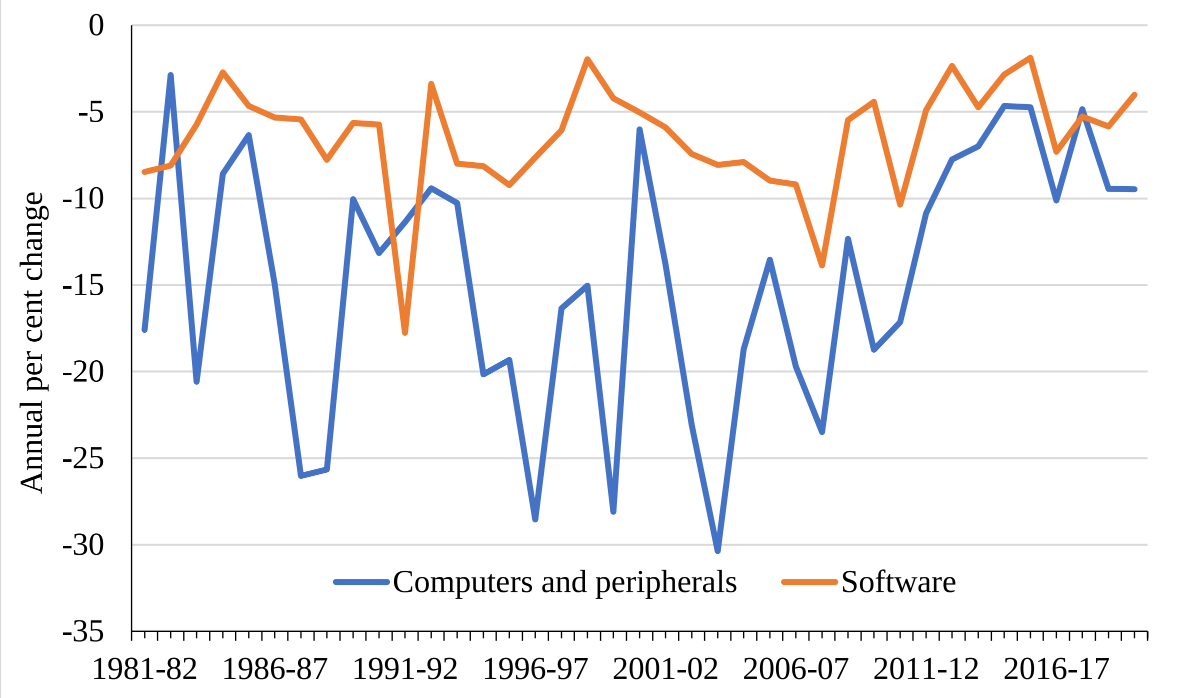
Appendix Figure 1: Characteristics of occupation groups, percentile deviations from median



Note: Average DOT percentiles constructed using 1986 employment weights. Excludes agriculture and the military.

Sources: Employment weights from ABS, 1986 Australian Census. Characteristics constructed from US Dictionary of Occupational Titles 1977.

Appendix Figure 2: Prices of IT-related equipment relative to GDP price deflator, 1981-82 to 2019-20



Note: Prices series are constructed as the ratio of an implicit price deflator for computers and peripherals/software and an implicit price deflator for GDP. Each implicit price deflator is constructed as the ratio of current and constant value investment series.

Sources: ABS, Australian System of National Accounts, Tables 5 and 70.

Appendix: Method for decomposing sources of changes in population shares of occupation groups

Formally, the basis of the method is an equation linking flows to changes in stocks:

$$Stocks_{t+1} = \rho_t \cdot Stocks_t \tag{A1}$$

$Stocks_t$ is a vector summarising the share of the population in each state: NRC, RC, NRM, RM, UE and OLF. ρ_t is a 6x6 matrix of flow rates between the states. The flow rate from state A to state B is equal to the number of individuals observed switching from state A at time *t* to state B at time *t+1* (3 months later), divided by the total number of individuals in state A at time *t* who are able to be matched to time *t+1*.

Suppose we are interested in knowing how the change in the flow rate for workers employed in RM occupations to OLF has affected the population share in RM occupations. To do this analysis, we compute a series of counterfactual stocks:

$$Stocks_{t+1}^{CF} = \rho_t^{CF} \cdot Stocks_t^{CF} \tag{A2}$$

ρ_t^{CF} is equal to ρ_t except we replace the actual value of the flow rate from RM to OLF at each time *t* with a counterfactual value equal to the average flow rate from August 1986 to November 1989. The years 1986-1989 are used as the counter-factual since it is at the start of the sample period, and importantly, those were years when the population shares for each of the six labour market states were relatively constant. The values of the population shares in August 1986 are used as the starting values for stocks for all labour market states. When the actual value of the flow rate from RM to OLF is replaced by the counterfactual value, the sum of flow rates out of RM will not equal one. To correct for this, the difference between the observed and the counterfactual rates is allocated proportionally to all other flow rates out of RM (the source labour market state) according to their relative magnitude. From this exercise we can obtain a simulated share of employment in RM occupations at the end of the sample period at time *T*. For our analysis, we end our sample period in February 2020, prior to the onset of COVID-19. The counterfactual change in the share of employment in RM occupations across the sample period is then calculated as:

$$\Delta RM^{CF} = RM_T^{CF} - RM_{1986} \tag{A3}$$

The final step is to define the fraction of the change in the share of population employed in RM occupations that would have been avoided if there has been no change in the flow rate from RM to OLF as:

$$1 - (\Delta RM^{CF} / \Delta RM) \tag{A4}$$

where ΔRM is the actual change in the share of population in RM occupations (equal to: RM_T - RM_{1986}).