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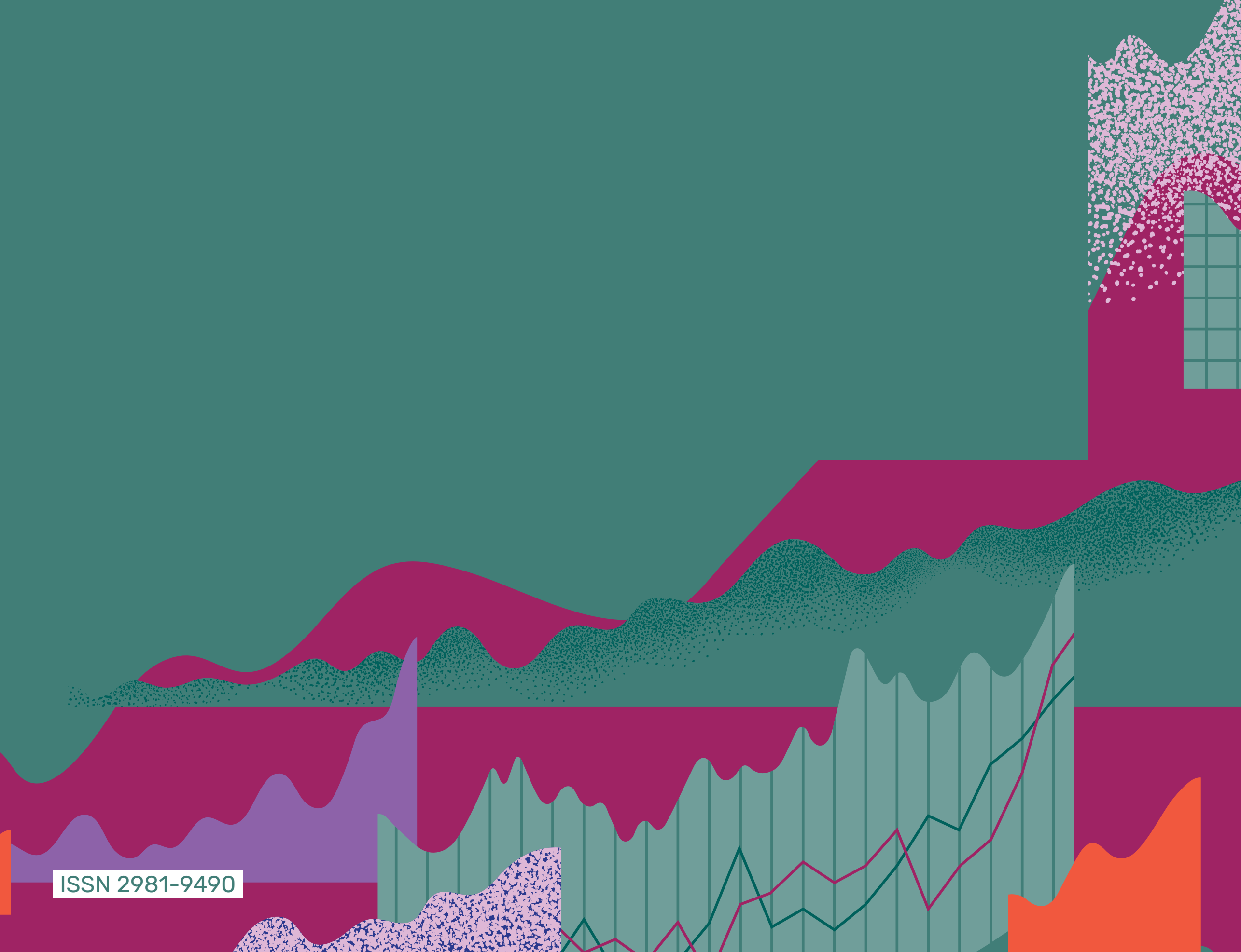

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From the Managing Editor

Welcome to the last issue of *AJLE* for 2024. As usual it contains a range of papers which are of interest to a varied audience interested in labour economics and labour market issues. This issue of the journal includes an article in our irregular series of articles by experts in the field covering topics of interest to labour economists, students and practitioners.

It has been a busy time at the *AJLE* organising the Australian Labour Market Research (ALMR) Workshop that was held in February in Canberra and hosted by Jobs and Skills, Australia and sponsored by the Australian Bureau of Statistics. The purpose of the Workshop is to disseminate high quality research in labour economics and labour relations and to promote informed public debate about current labour market issues. This year's Workshop certainly met this objective. Participants and discussants included senior academic economists and labour economists in the public and private sectors. Early career researchers, including PhD students close to completing, were particularly encouraged to submit papers and made up a healthy proportion of participants. Any theoretical, applied or policy related papers on any aspect of the labour market are welcome and the Workshop contained a good mix of papers of interest to researchers and practitioners in labour market issues and policy. We hope you will consider offering a paper for the next workshop – a notice will be coming out shortly.

The first paper in this issue is by Jeff Borland, of Melbourne University, and is based on his invited address to the recent 34th ALMR Workshop. Previous invited presenters have included ANU's Bruce Chapman, on Australian and international experiences of HECS-type funding of higher education, and Peter Dawkins, on the role of the labour economist in public policy.

Jeff's paper discusses an approach to understanding labour markets. He suggests an overall framework for analysing labour markets, and a detailed treatment of several elements. These consist of asking questions, how to think about the causes of changes in labour market outcomes, and using descriptive information to evaluate causality. The approach is illustrated through examples taken from his research on Australia's labour market during the COVID-19 era. Readers will find this paper thought provoking as it adds to the understanding of how to examine labour market issues for researchers and policy practitioners. Students will find the paper particularly instructive.

The paper by Stephen Robson and Jeffrey Looi of the Australian National University, and Martin Hensher of the University of Tasmania, examines the question of the extent to which artificial intelligence (AI) and virtual care (VC) can emulate the abilities of humans in delivering human-centred healthcare. It has been recognised for some time that current demographic trends in Australia, as in many other countries, have created debate on the provision of healthcare for an ageing population, and an ageing workforce, with a greater prevalence of chronic and degenerative disease, requiring new patterns of more complex care and health technologies. There is a fear that there will not be a sufficiently large enough workforce available for future healthcare needs or enough workers with the required skills. The paper provides an overview of how AI and virtual care are being introduced into healthcare services, and the potential for them to be applied more extensively in coming years. The paper obviously covers a critical topic which should be of interest to readers.

The paper by Robert Dixon, of the University of Melbourne, looks at a commonly quoted "rule" in economics, namely, Okun's law. This, broadly, maintains that there is an inverse relationship between output growth and unemployment. Robert's paper sets out a new approach to understanding Okun's law and the evolution of the unemployment rate in Australia. Rather than examine the changes in unemployment the paper examines the entry and exit rates to unemployment. The empirical analysis is employed to examine the extent to which the variations in one or both of these rates – entry and exit – can be explained by variations in GDP growth. There is found to be an observed asymmetry in the Okun relationship in that there is a greater impact of changes in GDP growth on the entry rate and not the exit rate. The behaviour of the entry and exit rates are such that in an economic downturn the unemployment to employment ratio rises relatively 'fast' while during the recovery the unemployment to employment ratio falls relatively slowly. This has implications for government intervention early in the onset of a recession.

I think you will agree that all the articles in this issue will be of interest to anyone researching or practising labour economics. I would like to thank authors, the anonymous referees and co-editors for their contributions to the *AJLE*. Once again special thanks go to the *AJLE*'s editorial assistant, Sandie Rawnsley, for doing an excellent job in making this issue possible.

Phil Lewis
Managing Editor

Understanding how the Australian labour market works, with examples from the COVID-19 era - A talk to the 2025 Australian Labour Market Research Workshop

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Abstract

This article is about how to understand labour markets. I suggest an overall framework for doing analysis of labour markets and give a detailed treatment of several elements: asking questions, how to think about the causes of changes in labour market outcomes and using descriptive information to evaluate causality. To illustrate these approaches, I use examples taken from my research on Australia's labour market in the COVID-19 era.

Acknowledgement: This article is based on the keynote presentation at the 2025 Australian Labour Market Research Workshop. It draws on two research papers in progress, Borland (2025a, 2025b). I am grateful to Phil Lewis for the invitation to present the talk, to participants at the Workshop for helpful feedback, and to Matt Cowgill, Bjorn Jarvis and Peter Lake for very helpful comments on a draft version of the article. All opinions and any errors are my own.

Introduction

In this talk I am going to change the pace. So far in the workshop we have heard lots of interesting and informative presentations on what is happening in Australia's labour market. I want instead to move back a step and make my focus the methods we use to get that knowledge about what is happening. Specifically, my central theme will be how we take the tools of economics and apply them to answer questions about the operation of labour markets.

My talk is in two main parts. First, I will introduce an overall framework for how to analyse labour markets. Second, I will address in more detail several elements from that framework. To illustrate my ideas, I am going to use content from my recent research on the Australian labour market during COVID-19.

Analysis of labour markets encompasses a range of purposes, types of questions and techniques. My concern in this talk is going to be with a category of analysis that I call 'policy analysis'. This category is purely my invention. But the features I attribute to the category, shown in Table 1, do I feel, represent a distinct stream of analysis.

What I have in mind is analysis to answer a question that is policy relevant at that time and is about a specific labour market. Policy relevant can mean questions that are directly about policy, or questions about what is happening in the labour market that are important background for policy making. My talk is going to mainly involve the latter type of question. Examples might be wanting to know what has happened to Australia's labour force participation rate in the past decade, understanding why nominal wage growth was so low in Australia in the 2010s, or evaluating whether there is currently a shortage of teachers in individual states and territories in Australia. It is my impression that it is this type of background question which is most prevalent in policy analysis of labour markets.

Policy analysis also brings a distinct approach to how it goes about answering these questions. That approach is primarily empirical, using descriptive statistics and perhaps simple regression analysis, integrated with a synthesis of findings from existing studies. Think of, as examples, an RBA *Bulletin* article, a Productivity Commission research report, or a Treasury *Round-Up* article. Government naturally is a major source of policy analysis of labour markets in Australia, along with researchers at think-tanks, academics and market economists.

Obviously, there are alternative approaches to labour market analysis. In Table 1, I compare the features of policy analysis against two other categories that might be identified, which I label as 'market analysis' and 'academic research'. My emphasis in distinguishing between the categories is on the questions asked and how analysis of labour markets is done, rather than who does the analysis. (For example, it is common these days for economists working in government to be doing what I classify as 'academic research'.)

Table 1. Types of labour market analysis

	Market analysis	Policy analysis	'Academic' research
Objective	Comment on narrow topic.	Answer question of policy relevance at specific time for specific country.	Original contribution of broad relevance to knowledge on labour markets.
Types of questions	Commentary on today's labour force figures. Description of trend in labour productivity.	What has happened to labour force participation rate in Australia in the past decade? Why is wage growth in Australia relatively low?	How does technology affect labour markets? How do childcare policies affect labour supply?
How analysis is undertaken	Presentation plus basic analysis of descriptive statistics.	Synthesis of existing knowledge plus new empirical research based mainly on descriptive statistics.	Original empirical (and theoretical) research.
Data used	Headline statistics	Detailed data underlying headline statistics plus some use of unit-record data.	Unit-record individual and firm-level data. Value placed on use of new data sources.
Output and audience	Short research note -> Clients, other market economists, other members of own organisation, media.	Report (of varying length) -> Other economists in own or other government departments and agencies, Ministers and staff. Sometimes external audience of professional economists through external publications. Media, business, researchers in other social sciences.	Working paper/Journal article -> Primarily other academic economists.
Causality	Usually not concerned with causal impacts.	Seek to argue for causal impact using existing knowledge and through careful interpretation of descriptive statistics and regression analysis.	Use advanced empirical techniques for identifying causal impact.
Time period	Needs to be done quickly to fit the purpose – usually just a couple of hours.	Could range from a week to several months, depending on scale of project.	Usually needs to be conducted over an extended period, with the original phase of research taking several months or longer.

To conclude this introduction, and summarise where I have got up to so far, my talk is going to:

- be concerned with questions about the labour market that arise in doing policy relevant analysis.
- suggest a structured approach to answering those questions.
- be about the practice of answering the questions – that is, how best to create bridges from technique to application.

Given this focus, I suspect the main audience for my talk is early career public policy and labour market analysts, as well as students intending on that career. At the same time, hopefully aspects of what I say will also be of wider value, for anyone undertaking labour market analysis.

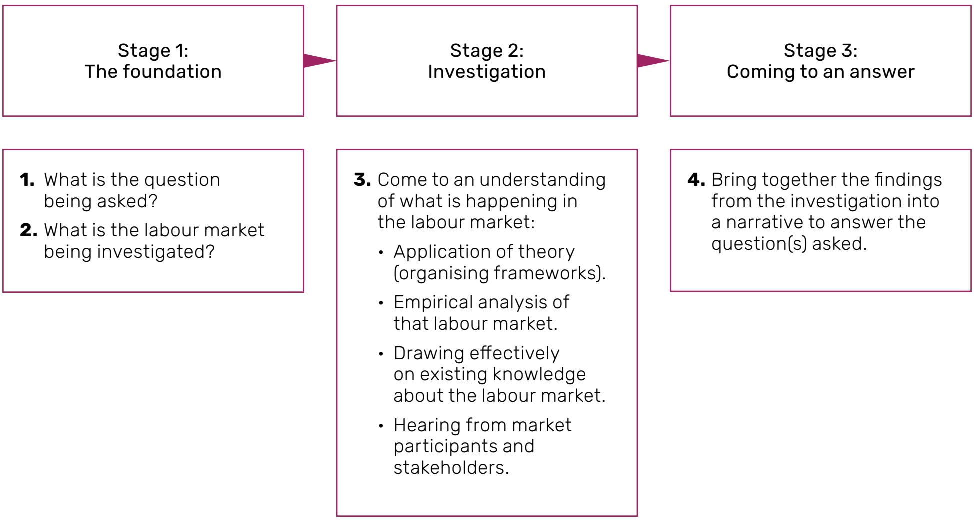
The overall framework for labour market analysis

What is the 'structured approach' for labour market analysis that I am proposing? Figure 1 provides an overview. Essentially, there are three main stages in the approach, which I classify as: (1) Foundation; (2) Investigation; and (3) Coming to an answer.

Stage 1 – The foundation

The starting point is to know the question you want answered and the labour market you are interested in. Having a well-formed question is essential. Without that there won't be any purpose or structure to your analysis. You may be given the exact question you will need to answer, or it may come from initially being asked to consider issues related to a broad labour market related topic, in which case getting to the question will be part of your task of analysis, and is likely to take some time. Defining the labour market you are analysing is also a must. Sometimes your question will imply directly the labour market you are interested in. But if not, this needs to be thought about explicitly. Is your interest in labour market outcomes for the whole of Australia, for an individual industry such as mining or manufacturing, or for a specific group of workers in a specific region, such as hairdressers in Victoria? Whatever the answer, how you define the labour market will set the scope of your analysis, suggest the types of influences on labour market outcomes you will need to consider, and likely also the data you should use in any empirical analysis.

Figure 1. A structured approach to answering questions about the labour market



Stage 2 – Investigation

The next step is to undertake an investigation directed at answering your question. This stage involves creating and bringing to bear on the question of a range of different types of information. This information can be derived from the application of economic theory, your own empirical analysis, the findings from existing studies that relate to the question, and via stakeholders and market participants.

For the information you collect through the investigation to have the greatest chance of leading you to a correct answer to your question, you will need a solid knowledge of (i) general ways of thinking about how the labour market operates, what I call 'frameworks for organising thinking about the labour market' and (ii) how to do empirical analysis.

Theories of how labour markets operate are many and diverse. But when it comes to answering policy analysis type questions, I would argue that those theories can be distilled to four core 'ways of thinking' about labour markets:

- Representing labour market outcomes as the **equilibrium** from interactions of the forces of demand, supply and institutions.
- Recognising the role of **drivers**. Having a taxonomy of the main channels through which demand, supply and institutions determine labour market outcomes.
- How changes in labour market outcomes imply **adjustment**. Representing changes in labour market outcomes as occurring through a process of adjustment, where that adjustment can potentially occur in multiple ways.

- The human element. How behaviour and outcomes in a labour market depend specifically on the fact that it is the labour of humans that is being traded.

By 'how to do empirical analysis', at a high level I mean a knowledge of empirical techniques relevant to answering policy analysis type questions about labour markets – including skills in measuring, describing, and assessing causality. At the coalface of doing empirical analysis, this translates into a plethora of specific skills. These skills range from what might be seen as the very basic, such as being able to correctly interpret the meaning of variables and generate descriptive statistics, through to the advanced, including the ability to manage large data sets and apply sophisticated econometric techniques.

Stage 3 – Coming to an answer

Ultimately, you will need to use the information you collect in your investigation to come to a judgement on the answer to your question. To do that will require you to collate and interpret your information, and to use that as the basis for your answer. The final step is to present your answer and supporting evidence to whoever has asked you to do the analysis, in a format they have asked for or that you choose.

For the rest of the talk, I will draw from this suggested structure to describe three key elements of doing labour market analysis. These are:

a. Begin with a question and keep asking questions
b. Know the drivers and follow the consequences, and
c. How to judge causality

a. Begin with a question and keep asking questions

My claim is that there are four types of questions that get asked about labour markets. The first two types, with which I am mainly concerned in this talk, are what I call 'describe' and 'explain' questions. *Describe* questions ask for a description of an outcome or outcomes occurring in a labour market (or markets). *Explain* questions ask for the reason(s) that an outcome has occurred. In addition, there are two other types of question that might be asked. *Policy* questions are about whether a situation has arisen where government intervention in the operation of a labour market can improve society's wellbeing, and what that intervention should be. *Prediction* questions ask what will happen in a labour market in the future. Table 2 gives examples of each type of question.

Table 2. Analysis of labour markets – The types of questions that get asked

Type of question	Definition	Example
a. Describe	Questions asking about what outcomes are occurring in a labour market (or markets):	
	What outcome(s) are occurring at a point in time?	What is the proportion of the labour force in Australia is currently unemployed?
	Whether a difference exists in some outcome between groups of workers in the labour market or between workers in different labour markets at the point in time?	In the 2021 Australian Census, what was the average hourly wage of workers with a bachelor's degree compared to workers who did not complete high school?
	Has an outcome changed over time?	What has happened over the past year in Australia to the proportion of the workforce who move between jobs?
	Is there a difference in changes over time?	What has happened over the past year to the labour force participation rate in Australia compared to the United States?
b. Explain	Why has an outcome happened?	Could, for example, be applied to the findings from any of the 'Describe' questions – such as: What explains why the average hourly wage of workers with a bachelor's degree is higher than for workers with no post-school qualification? What explains why the proportion of the workforce who moved between jobs has increased over the past year?
c. Specify implications for policy	Is a policy response needed to address an outcome that has occurred? If so, what should that policy response be?	Could, for example, be applied to the findings from any of the 'Describe' questions – such as: Is the current rate of unemployment too high or too low? If so, what policy response is needed to alter the rate?
d. Predict	What outcome(s) will occur in future time periods?	Will the rate of unemployment in Australia increase? In which Australian regional labour markets will there be the largest impact from decarbonisation?

Any analysis must, at some stage, arrive at a question to answer. Because it is only when you get to a question that your analysis can have direction. That is the sense in which you should always 'begin with a question'. Having in mind the four types of questions can assist you in doing this. Needing to put your question into one of the categories will make you think exactly about what it is you want to know and allow you to be more precise in expressing your question. Identifying the type of question you are asking can also help to point you in the direction of the empirical methods you will need to use.

The original question is your main question, and the one that you always need to come back to. But doing analysis is almost never as simple as answering just one question. Usually, in the process of seeking to answer the question you commenced with, extra questions will come up, that you will feel you need to answer in order to be confident about or to fully understand the answer you give to the main question.

For a *describe* question, that follow-up question might be: 'Will I find the same outcome if I use a different data source, or if I compare with a different country, or if the weighting I have used to create my key variable is done differently?'

For an *explain* question, it might be that having found that your original hypothesis to explain an outcome does not work out, you need to go on to consider other potential explanations. Or even if your original hypothesis does work out, every cause has its own cause, so you may want to go to the next stage of investigating what is behind the initial causal factor you investigated.

In this way, understanding labour market outcomes most often requires you to form and answer a sequence of questions. In fact, in most analyses that you undertake it will be the case that you could go on asking extra questions forever. The issue is knowing when to stop, realising when you have reached the point where you know enough to answer your main question with sufficient detail and rigour.

There is no single right way to decide on the extra questions that should follow from the main question you begin with. But there are guiding principles you can follow. *First*, the objective in asking more questions is to add to your knowledge. So, you should try to think of follow-up questions that are going to add most to being able to answer your original question. *Second*, the type of questions that are likely to add usefully to your knowledge almost always relate to the context of your analysis: the specific question you began with, the data and variables you are using, what theory says, how policy might be applied, and what is already known. *Third*, generally there will be multiple approaches to asking extra questions that will add to your knowledge that are relevant to the main question you begin with. That makes them all potentially worth pursuing, and choosing among them will come down to your judgement.

Here is an illustration of labour market analysis as a sequence of questions, drawn from my study of the Australian labour market during the COVID-19 era. The issue of labour market tightness has been of significant interest to policymakers from around late 2021. A standard measure of tightness is the vacancy rate, and no doubt a question that many labour market analysts have been asked in the last several years is: what has happened to job vacancies in Australia during the COVID-19 era? The answer, shown in Figure 2, is straightforward: the vacancy rate has skyrocketed. Not only that, but even in late 2024 it remained well above historical levels.

Figure 2. Job vacancy rate, Australia, May 1979 to November 2024 (quarterly; sa)

Notes: Calculated as (Vacancies)/(Vacancies + Employment).
Source: (i) Vacancies – ABS, Job Vacancies Australia, Table 1: (ii) Employment - ABS, Labour Force Australia, Table 1.

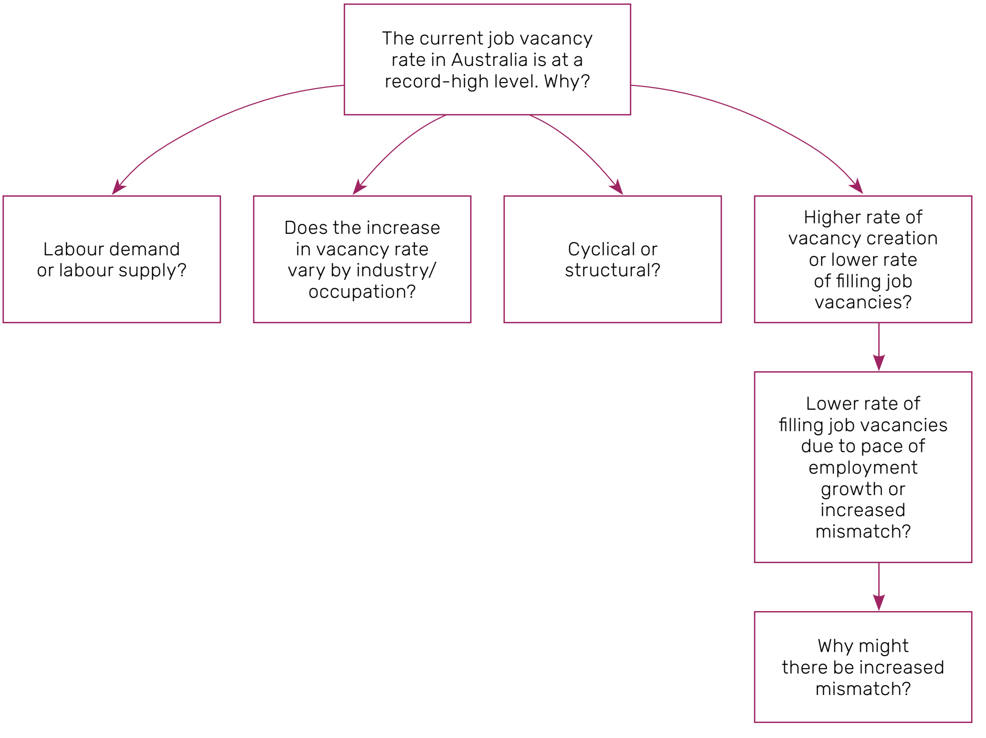
Knowing that the vacancy rate hit such heights and remained elevated leads naturally to a next question: Why?' To be able to answer that question, it is necessary to think of possible explanations to be investigated. Figure 3 shows some of the different ways this could be done.

You might try to look at the extent to which the higher vacancy rate has been due to growth in labour demand or to restrictions on labour supply, such as lower migration inflows. You might study changes in the vacancy rate by industry or occupation, with the idea that those patterns would suggest potential explanations. Or you might analyse the Beveridge curve relation between vacancies and unemployment to understand to what extent the higher vacancy rate reflects cyclical or structural influences. It is a matter of judgement what to do.

In my analysis, I chose to ask as the next question to what degree the high vacancy rate at the end of 2024 was due to: (i) a higher rate of creation of new job vacancies or (ii) vacancies being filled at a slower rate. I did this because I anticipated that answering that question would directly feed into a further question, that could get me close to having a sufficiently precise answer to the question of why the vacancy rate remained so high. That was borne out as I did the analysis.

Having discovered that the high vacancy rate at the end of 2024 was mainly due to vacancies being filled more slowly, I was able to use that finding to ask as a follow-up question: What were the relative roles of the rapid pace of employment growth in Australia and labour market mismatch in explaining the high vacancy rate? And with the answer to that question in hand, I was able to go on to also ask why there might be higher mismatch in the labour market.

Figure 3: Labour market analysis as a sequence of questions



I am not suggesting that my sequence of questions turned out to be more informative than alternative ways in which the 'why' question might be asked. What is important though is that I had an argument to justify how my line of questioning would add to my knowledge in a way that was useful for understanding the elevated vacancy rate at the end of 2024. That made it worthwhile to pursue the line of questioning. No doubt fully understanding why the vacancy rate remains so high also requires pursuing alternative approaches to asking additional questions.

b. Know the drivers and follow the consequences

Economists bring a standard approach to thinking about how changes in market outcomes occur. For the analysis of labour markets, this way of thinking can be translated as:

- Labour market outcomes, such as wages and employment, are causally determined by a set of 'drivers'. Those drivers consist of the main forces that affect labour demand and labour supply, together with institutions and policies.
- It follows that changes in the drivers give rise to changes in labour market outcomes. Or put the other way around, labour market outcomes adjust in response to changes in the drivers in a market.

All this really means of course is that economists use models to understand markets, and when you change exogenous variables in a model, you get different predictions for the endogenous variables. However, recognising that this is how we think does, I would argue, have an important implication for doing labour market analysis: If you are going to analyse labour markets, it is valuable to carry round in your head (i) a list of the potential **drivers** operating on any labour market and (ii) a list of potential labour market **outcomes** – that is, the ways that adjustments can occur in a labour market.

I will now spend some time discussing each of these 'lists'.

Drivers

Different drivers cause different causal impacts on labour market outcomes. For that reason, to understand adjustment in labour market outcomes, you must be able to precisely identify the drivers that have changed. This requires being aware of the set of potential drivers, which is a lengthy list.

Tables 3a and 3b present my summary of major drivers of labour market outcomes. The tables classify drivers between those that directly affect labour demand and/or labour supply, and those that derive from economic policy. Both tables also further divide each category according to the duration over which the driver impacts on the labour market.

Table 3a. Drivers that directly affect labour demand and/or labour supply

Time horizon	Examples of type of driver	Main features
Long run/Tectonic	Technological change Climate change Demography Social norms Globalisation Educational profile of workforce	Slowly evolving and continuous incremental permanent impacts over a long time period
Long run/One-shot	Change in labour supply preferences (e.g., from learning new information about benefits of working from home)	Large permanent impact that commences at time of change in driver
Medium run	Mining boom COVID-19 Extended extreme weather event (e.g., drought over several years) War/international conflict	Large temporary impact concentrated in a time period of several years
Short run	Short-term extreme weather events (e.g., cyclones) Regular seasonal cycle Strike activity	Large temporary impact concentrated in a limited time period (e.g., a few months)

Table 3b. Policy drivers

Type of policy	Main features
Policies subject to ongoing reform to address long-run drivers (e.g., climate change policy; education and training policy)	Slowly evolving and continuous incremental permanent impacts extending over a long time period
Monetary and fiscal policy to manage business cycle	Large temporary impact concentrated at time of policy implementation
One-off policy reforms that affect labour market e.g., reforms to IR system; minimum wage; immigration policy; childcare policy; income support payments; public sector employment policy	Large permanent impact concentrated at time of introduction of policy

Outcomes and adjustment

Understanding labour market outcomes and adjustment requires being able to characterise the set of labour market outcomes that might alter when a driver changes, knowing what are the causal mechanisms that connect a change in a driver to a labour market outcome and appreciating the linkages that can exist between labour market outcomes.

I will now say something more about each of these aspects.

The set of labour market outcomes

Once you start thinking about what might be considered as a labour market outcome, you quickly realise it is a broad set. Table 4 lists a set of potential outcomes, taken from the excellent overview of adjustment in labour markets by Richard Blandy and Sue Richardson (1982).

Table 4. Labour market outcomes – Margins of adjustment when drivers change
Average pay level
Monetary and fiscal policy to manage business cycle
Relative pay (e.g. between new hires/incumbent workers; by occupation; between firms)
Total employment
Average hours worked
Entry requirements/Hiring standards
Rates of promotion within organisations
Characteristics of jobs
Rate of worker turnover/Worker tenure
Extent of occupational/industry mobility
Incidence of self-employment
Labour force participation
Worker training and acquisition of skills
Job search effort
Rates of flow between labour force states/Rate of job-to-job transitions

Source: Blandy and Richardson (1982)

Blandy and Richardson's list suggests that a thorough analysis of the impact of a change in a driver will often require investigating an extensive set of labour market outcomes. As a case study, we can look at the array of ways in which labour markets might adjust to an increase in the minimum wage, as summarised in recent work by Arindrajit Dube and Attila Lindner (2024). For a long time, research on the minimum wage pretty much exclusively looked for effects on employment. That has changed in the past decade, with a much broader potential set of modes of adjustment now being considered. The modes of adjustment reviewed by Dube and Lindner are: Changes in total employment, the composition of employment by full-time/part-time status, job amenities, worker turnover, worker productivity, the composition of workforce by skill level and labour force participation are the main margins of adjustment considered (as well as non-labour market outcomes such as firm entry and exit, output prices and profits).

Causal mechanisms

The way we think about labour markets needs to be soundly based. If we are going to suggest a linkage between a change in a driver and adjustment in a labour market outcome, we want there to be a causal basis for that association. To believe a causal relation exists will depend on both theory and empirical analysis.

Let's continue with the example of an increase in the minimum wage. Critical to thinking it worthwhile to study the modes of adjustment suggested by Dube and Lindner is that the economic theories of labour demand by a profit maximising firm and/or labour supply by a utility maximising household provide a basis for believing there is a potential causal relation between an increase in minimum wage rate and those outcomes. We know, for example, that reducing the quality of job amenities, hiring higher productivity workers or substituting workers being paid the minimum wage for other types of workers or capital, are ways that a profit maximising firm facing a requirement to pay a higher minimum wage might adjust.

Theory therefore provides the basis for identifying and investigating each potential causal relation from an increase in the minimum wage. To believe that a causal relation actually does exist with any of the outcomes suggested, it is necessary to go further and undertake empirical analysis that finds evidence in support. One example where this has happened is from quantitative studies of the impact of minimum wages on worker turnover, that almost universally finds a significant negative causal relation (Dube and Linder, 2024, Table 5).

Linkages between labour market outcomes

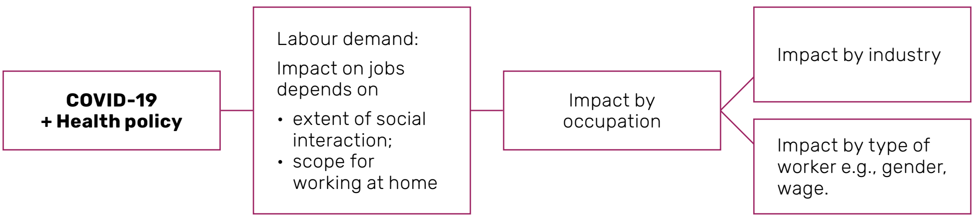
It is important to appreciate that changes in labour market outcomes may themselves be linked, often a further essential element to understanding adjustment. Continuing again with the minimum wage example, an increase in the minimum wage may cause firms to substitute away from workers paid the minimum wage towards other workers. If that substitution effect is widespread enough, the increase in the demand for the labour of the other workers may be sufficient to cause an increase in their wages. That is, the increase in minimum wage rate is linked to an increase in the pay of higher wage workers. Appreciating the breadth of the potential linkages between labour market outcomes, which I refer to as 'seeing the labour market whole', is vital for understanding how adjustment happens.

To illustrate the importance in labour market analysis of knowing the drivers and being able to follow adjustment, I will use as my example the initial impact of COVID-19 on Australia's labour market.

The spread of COVID-19 within Australia in March 2020, combined with growing awareness of rapidly developing health disasters in other countries, was the background to its immediate impact – a 'shutdown' of economic activities, caused by government-imposed restrictions on travel and mobility and prohibitions on activities that risked transmission of COVID-19, together with voluntary withdrawal by consumers from some activities. It was this shutdown of economic activities that was the main driver of the impact of COVID-19 on Australia's labour market in early 2020.

Identifying that shutdown was the main driver of what happened in the labour market – and this is the critical point I want to make – then allows us to trace out how employment outcomes adjusted. Figure 4 presents a flow-chart summarising this adjustment, focusing on the impact of shutdown on labour demand. (Breunig et al., 2024 identify labour demand as the main channel of transmission to employment outcomes).

Figure 4. Understanding the initial impact of COVID-19 on employment



The start of the flow chart recognises that the most direct immediate impact of COVID-19 was on labour demand at the job-level. Restrictions imposed on travel and mobility implied a concentrated negative impact on labour demand in jobs where there was not a capacity to perform that job at home. That negative impact was intensified in jobs with a high level of social contact, which were in addition adversely affected by government prohibitions and voluntary withdrawal by consumers. Table 5 demonstrates how this impact played out in the pattern of decreases in employment by type of job in the earliest phase of the pandemic, using 4-digit occupations to represent jobs.

Table 5. Job-level impacts of COVID downturn by extent of social contact and scope to work at home

Type of job	Change in persons employed, Feb to May 2020 (%)	Examples of jobs
Low scope to work at home plus high social contact	-13.3	Early childhood teachers; physiotherapists; general practitioners; bricklayers; chefs; hairdressers; waiters; mail sorters
Low scope to work at home plus low social contact	-6.8	Engineering managers; land valuers; surveyors; safety inspectors; motor mechanics
High scope to work at home plus high social contact	-0.2	Primary school teachers; university lecturers and tutors; call centre workers
High scope to work at home plus low social contact	-1.7	Graphic and web designers; urban and regional planners; software and applications programmers

Source: Borland (2025a)

This impact on jobs translated into an impact on the distribution of employment between broader occupation categories, the next stage in the flow chart. Differences in how types of jobs (4-digit occupations classified on the basis of scope to work at home and extent of social contact) are distributed across broader occupation categories (1-digit occupations) meant that the shutdown due to COVID-19 differentially affected employment in the broader categories. The most adversely affected 1-digit occupations were community and personal service workers, salespersons and labourers with professionals being least affected.

In turn, because the occupational composition of employment differs between industries and across workers by demographic and job characteristics, an unequal impact of the pandemic between occupations also implied unequal impacts on employment on those other dimensions. These are the final stages in the flow chart.

The impact on employment by worker characteristics is shown in Table 6. Females were more negatively affected than males, reflecting their greater concentration in the most adversely affected occupations. For the same reason, young workers were much more adversely impacted than mature age or older workers. Casual employees were more negatively affected than permanent employees. This likely reflected the larger share of casual employment in the most affected occupations, as well as casual employees with less than 12 months tenure being ineligible for the Job Keeper program.

Table 6: Impact on employment, By worker characteristics, Early 2020

	Change in employment	Share of employment in 3 occupations (1-digit) most negatively affected by COVID-19 (%)
1] Sex	*Change in monthly hours – March to May 2020 (%)*	*Feb. 2020*
Males	-8.7	23.4
Females	-12.5	28.9
2] Age	*Change in weekly hours – March to May 2020 (%)*	*Feb. 2020*
15-24 years	-23.4	57.9
25 plus years	-8.1	24.5
3] Employee status	*Change in weekly hours – February to May 2020 (%)*	*Feb. 2020*
Permanent	-6.1	22.3
Casual	-27.0	46.2

Source: Borland (2025a)

Two important themes about drivers and adjustment are illustrated from the example of the immediate impact of COVID-19 that I have just worked through:

First, it demonstrates how knowing the driver(s) is critical for tracing out adjustment. In this example, identifying the driver as the shutdown of economic activities allows us to see a direct causal link from onset of COVID-19 to the pattern of adjustment in employment outcomes.

Second, it shows the importance of 'seeing the labour market whole'. Recognising the links between alternative labour market classifications enables us to appreciate how the initial direct impact of COVID-19 on the composition of employment by job type would have implications for the composition of employment by occupation, industry and between workers with different demographic and job characteristics. Those impacts on the different types of employment outcomes were simultaneous, since each outcome is just a different way of classifying employment at the same point in time. Hence, in this case 'following adjustment' is about specifying a logical structure for understanding a set of changes that happened simultaneously. In other cases, 'following adjustment' may be more about setting out a path of adjustment in outcomes that occurs over time with, for example, a change in a driver causing a change in a labour market outcome, which itself causes a change in another outcome.

c. How to judge causality

Establishing the causal relations that exist between drivers and outcomes in a labour market is at the core of labour market analysis. It is central to answering *explain* and *policy* questions and is also relevant to *predict* questions. These days, the mention of causal relations immediately brings to mind 'program evaluation' techniques such as randomised controlled trials, difference-in-difference, regression discontinuity and instrumental variables techniques. Increased application of these methods underlies what is often referred to as the 'causal revolution' in micro-econometrics and has brought a significant increase in the rigour with which causal relations can be identified. Seminal contributions were made by David Card (1990), and Josh Angrist and Alan Krueger (1991). (For a recent review see Garg and Fetzer, 2025.)

The problem for our purposes, however, is that for many (maybe most) policy analysis type questions we want to answer about the labour market, program evaluation techniques cannot help us at all, or will only get us so far. This is because for many questions it is likely that no (or only limited) relevant empirical evidence from program evaluation techniques will be able to be generated. This could reflect the nature of the question not being amenable to those techniques, or data limitations or time constraints that prevent you using those techniques. When this happens, descriptive information, facts about the labour market derived from descriptive statistics and simple regression analysis, become the primary source of empirical evidence that can be applied.

So, how should we proceed if we want to determine whether a causal relation exists between a potential driver and a labour market outcome, and we need to use descriptive information to do that? Suppose for example that we have been asked to analyse whether increased opportunities for female participation in higher education have had a causal impact on female labour force participation, and to determine the magnitude of any such impact. How can we go about answering this question?

We need to begin by collecting the information on which we will rely to answer the question. I would suggest several strategies for doing this:

First, begin with theory. Establishing that there is a plausible theory for a causal relation between the variables being analysed is an essential step. Without a theory for a causal relation that is consistent with our conception of how humans behave and interact, it is impossible to fully believe that such a relation exists. Meeting the standard of plausibility will depend on whether aspects of the theory such as the assumptions made and the channels through which causality is depicted as operating, themselves seem plausible. But while theory is therefore a necessary condition for believing a causal relation exists, it is rarely (if ever) a sufficient condition. Economists are notably inventive when it comes to thinking up plausible explanations for causal relations between variables, so we would usually like confirmation from data. Not only this, but theory also has limits. While it may give us confidence a causal relation exists between variables, it may not, for example, tell us anything about the strength of that relation.

So, second, we need to move on to look at data. Specifically, we want to do analysis that I am assuming needs to be undertaken using exclusively descriptive information that is available and relevant to the causal relation we are investigating.

The important point I want to make is that when we use that descriptive information in a directed way, it can inform us about causality. We are all familiar with the expression 'correlation is not causality'. But my own feeling is that this blanket rejection of using correlation to understand causality goes too far. Carefully directed analysis of correlation can in fact be valuable.

What do I mean by 'carefully directed'? I have in mind using descriptive information to investigate for causal relations: *first*, by applying what is known about the channels through which a causal relation would be expected to operate; and *second*, by applying simple principles underlying causality.

To illustrate the first point on causal channels, we can use my hypothetical investigation into whether female participation in higher education is causally related to female labour force participation. My argument is that it is possible to do better than, for example, just looking at a correlation over time between national-level aggregate outcomes for those two variables.

We could instead begin by asking: Which females have increased access to higher education and for which courses? Once we know that information, we can work out what it implies about the groups of females who we should observe to have higher labour force participation, and which types of jobs they should be doing. For example, where increased access to higher education is focused on females from low socioeconomic status groups, any direct causal impact on labour force participation should be for the same group. Or if increased access to higher education is for groups doing specific courses, any causal impact should primarily be reflected in higher participation by females working in occupations that those courses qualify them for. Looking more precisely at the relation between female higher education and labour force participation in the way I am suggesting may not exactly identify a causal relation, but it certainly gives more confidence of a causal relation than looking at correlation in national aggregates.

The underlying principle here is to use logic and/or theory to develop more detailed ways to test for causal relations using descriptive data. As Robert Abelson (1995, p.183) writes: 'A powerful strategy is to spell out the details of the causal mechanism… and then test the consequences this mechanism would entail.'

There is another set of questions relating to causal implications that could also be asked. This is to ask what else we might expect to observe happen, if there is a causal relation. For my example this would involve asking: Are there other outcomes we would expect to see if there is a causal relation between female participation in higher education and female labour force participation? One such implication could be for wages. If increased female labour force participation is being driven by increased higher education participation, we should expect to observe an increase in average female wages.

My second point is that whether descriptive statistics are consistent with basic principles underlying causality can be informative for supporting the existence of a causal relation. My hypothetical example can again illustrate. If education participation is truly driving labour force participation, the former must happen before the latter. That is, there is a timing element that can be part of our test of causality – as Austin Bradford Hill (1965) puts it in his list of checks for causal relations, the horse must come before the cart. There are other similar checks relying on principles of causality we could also apply. Other things equal, if a causal relation exists, we would likely expect that a larger increase in female education participation should give rise to a larger increase in female labour force participation. Similarly, we would expect that there should be a consistent impact across time for different cohorts of females for whom there is increased access to higher education.

One final point about doing your own empirical analysis to assess causality using descriptive statistics. My focus in this discussion has been on how descriptive statistics can be used to identify and therefore test causal relations. Other factors, though, must also come into play when you judge the credibility and relevance to your question of the findings from the analysis you do – such as data quality and how close the available data get you to your question, as well as the statistical and economic significance of what you find.

The **third** strategy is to use existing evidence effectively. It is likely that there will be existing studies with findings that relate to the question about a causal relation you want to answer. It is important to incorporate that evidence into your analysis – depending on your judgement as to its relevance and credibility.

The **fourth** strategy is to be willing to cast a wide net in your investigation, beyond using quantitative methods or to looking at the literature. Talking to stakeholders, people involved in the labour market you are studying, is an essential complement to the other strategies. As a pioneer of the field of labour economics, Clark Kerr, wrote (1988, p.38): 'Experience something of reality first hand, as well as second hand through statistics.'

There is a reason why an important part of any Productivity Commission inquiry is to talk to market participants and allow for public submissions, why Treasury and the Reserve Bank have business liaison programs, and why Jobs and Skills Australia has such an extensive structure of engagement with business, unions and educators (on this latter example, see Dawkins, 2024). It is the market participants who can tell you about institutional details, about the aspects of outcomes that cannot be captured in data, and about their own motivations and those of other stakeholders.

Many of my own examples of when it is been critical to hear from stakeholders involve understanding the impact of labour market policies. Twenty years ago, in a team analysing the Mutual Obligation Initiative, we only understood why the proportion of income support recipients doing the program was much less than expected, once we talked to the Centrelink case managers in charge of administering the program. More recently, as part of the Economic Inclusion Advisory Committee, I have learned that it is simply impossible to understand the inadequacy of the current level of JobSeeker payment without hearing from people receiving the payment about their lives.

Using information to answer the question

Applying these four strategies I have suggested – looking at theory, using data, reviewing existing evidence and talking to market participants – you will have the information which you now need to use to decide if a causal relation exists. How should you do that? What you cannot do is to plug the information into an algorithm or mathematical formula that will tell you the answer. Instead, it is going to be up to you to come to a judgement, justified by your interpretation of the evidence.

There is no single correct way to come to a judgement. But I do think there are practices to follow that will make for a judgment that best reflects and is justified by your evidence.

These practices are for you to:

- Make a complete and fair minded summary of the available evidence as it relates to the question about causality you are investigating.
- Weight each piece of evidence according to its importance for answering your question (where importance depends on credibility and relevance).
- Give an integrated, logical and as coherent as possible account of what the separate pieces of evidence imply for the answer to your question (accepting that often it won't be possible to entirely resolve inconsistencies). While you will ultimately need to be able to give this account in words, graphical methods can be a useful tool for mapping out the set of evidence and assessing causal relationships; see for example, Hernan and Robins, 2024, chapter 6.
- Present your answer, which should follow directly from your account of the evidence, always being willing to indicate your degree of uncertainty and what extra evidence might be valuable.

I think it is this sort of approach that John Kay and Mervyn King (2020, p.410) have in mind with their concept of narrative reasoning:

> 'Narrative reasoning is the most powerful mechanism for organising our imperfect knowledge. Understanding the complex world is a matter of constructing the best explanation – a narrative account – from a myriad of little details and the knowledge of context derived from personal experience and the experiences of others.'

To finish up on this topic, and to illustrate the role that the directed use of descriptive information can play in thinking about causality, I will again use an example from my study of the Australian labour market during COVID-19, this time about the 'great resignation'.

A rising job quit rate and apparent increase in the incidence of retirement in the United States in 2020 was interpreted as revealing a fundamental change in attitudes to work – and to portend the global spread of mass resignation and retirement. The enthusiasm for a 'great resignation' spread to Australia, and once the Australian Bureau of Statistics (ABS) released its *Participation, Job Search and Mobility* survey data for the year ending February 2022, showing a jump in the rate of job leaving, mania took hold – with headlines such as 'The Great Resignation hits Australia…' and 'Evidence of Great Resignation Emerges'. But did the rise in job leaving really represent a change in attitudes to work?

To test this causal proposition, let's start with theory. The theory of labour supply tells us that a change in attitudes to work is indeed a possible explanation for the rise in job leaving. If (some) people increase their preference for leisure over consumption, we would expect to observe a higher proportion of workers leaving their jobs. However, there is an alternative perspective, from the theory of labour demand. Stronger economic conditions mean a higher rate of new job creation. New jobs are filled in part by individuals coming from outside the labour force, but also by current workers. The rate of current workers leaving their jobs (to take new jobs) increases when labour market conditions improve, as was happening in Australia in 2021. Hence, theory also suggests a different explanation; and it is worth noting, an explanation that is supported by extensive existing empirical evidence on procyclicality of job leaving – for Australia, see D'Arcy et al. (2012, p.5). Even with regard to labour supply, an extra consideration is that a strong motivation for moving out of work that existed in United States, to avoid becoming ill with COVID-19, should not have affected behaviour as strongly in Australia.

Having alternative theories means we need to move on to empirical analysis, using descriptive information. We can begin with the aggregate measure of job leaving, shown in Figure 5. Looking at the series it is easy to see the jump in year to February 2022, and then also to February 2023. But what is apparent as well is that the rate of job leaving had been well below norm in the year to February 2021, and in the year to February 2024 largely reversed from the higher rates in preceding years. In assessing the size of jump it is also important to be aware of the strength of growth in labour demand in Australia at that time.

What should we conclude from this? I would argue that the aggregate evidence is not consistent with a change in labour supply (great resignation) explaining the increase in job leaving rate. First, it seems that the jump in job leaving in the years to February 2022 and 2023 job leaving can be explained by more regular features of the labour market: delayed catch-up to job leaving being below-norm in the year to February 2021 and strong employment growth in 2021 and 2022. Second, the turnaround in job leaving in the year to February 2024 seems to contradict the idea of a permanent change in preferences for working or at least shows it to have been a limited phenomenon.

Figure 5. Annual rate of job leaving, Australia 2015 to 2024

Source: (a) Employed persons who left a job in last 12 months - ABS, Job Mobility; (b) Number of persons who held a job in last 12 months – ABS, Participation, Job Search and Mobility Microdata, Table 1.

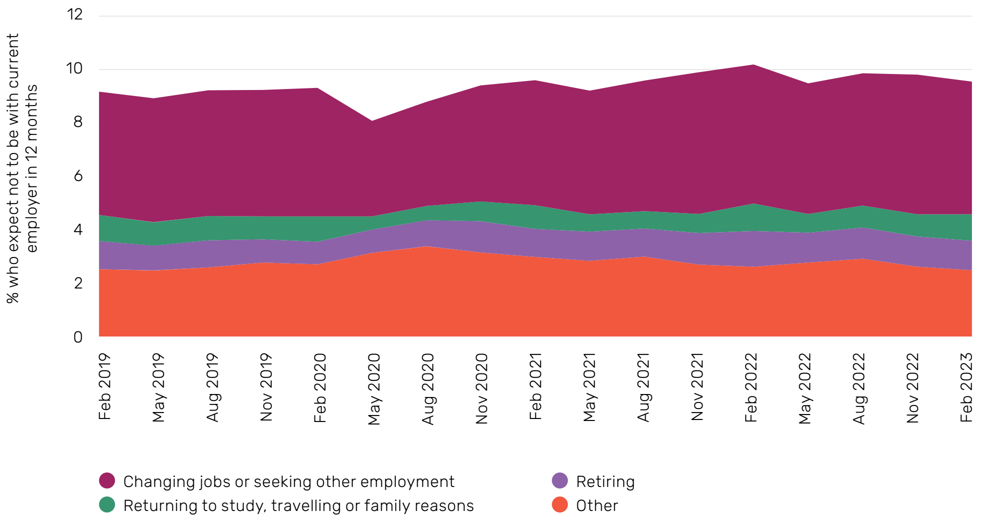
But we don't just have to rely on aggregate data, it is also possible to do a set of more directed analyses:

First, current outcomes can be compared against the longer history of job leaving, to give extra context. Doing this reveals that the type of down and up in job leaving observed during the COVID-19 era has been a common feature going back to 1980s and supports the idea that the job leaving rate rises during periods of strong growth in labour demand.

Second, an implication of the theory supporting the great resignation was that job leavers would move out of the labour force, rather than to another job. Hence, if the great resignation had been the powerful force claimed, a decrease in the labour force participation (LFP) rate should have occurred. But contrary to that prediction, we observe that the LFP rate, in aggregate and for all age groups, rose during the period in which the great resignation was supposed to be happening. In December, prior to COVID-19, Australia's LFP rate had been 65.7 per cent, but three years later, in December 2022, at the time when the impact of great resignation was supposed to be peaking, the LFP rate had grown to 66.6 per cent.

Third, it is possible to look specifically at motivations for job leaving. Job leaving due to the great resignation should have been associated with more workers quitting for reasons of wanting to do other activities, rather than, for example, their current job ending. However, using data from the ABS Labour Force Survey on workers' expectations of remaining with their employer over the next 12 months, shown in Figure 6, it can be seen that the slight increase in expectations of job leaving during 2021 and 2022 was mainly due to a larger proportion of workers expecting to quit to change jobs or seek other employment.

Figure 6. Proportion of persons in employment who expect to be with current employer/job in 12 months, by reason, February 2019 to February 2023



Source: ABS, Labour Force Australia – Detailed, Table 17.

What I have just presented is a combination of theory and set of descriptive analyses relating to whether the great resignation was real; that is, due to a change in labour supply. The judgement I come to from looking at that evidence is that the rise in job leaving in 2021 and 2022 was due to the cycle in labour demand, and not to a change in labour supply. That is, no great resignation.

How did I come to this judgement? It is the volume and consistency of the evidence: the movement in aggregate job leaving being consistent with the labour demand explanation, and the failure to find evidence supporting alternative implications of the great resignation (such as a decrease in labour force participation) or of the causal channel through which the great resignation would be expected to operate (such as leaving to study or travel).

Conclusion

This has been a presentation about method. Of course, in the end, the method of analysis is just the means to what really matters: the extra knowledge about the operation of the Australian labour market that our analysis brings. Still, the quality of what we learn depends hugely on the quality of the methods we apply – and there is nothing automatic about choosing those methods. That is why I think it is worthwhile for us every now and then to step back and try to say what our methods are, and what constitutes good practice. This must be more than a listing of the available technical tools, such as econometric estimators and our theoretical models of the labour market. Rather, it has to be about the ways we can or should apply those technical tools (together with our other skills).

We have a question, how are we to go about answering it? Hopefully, my talk will have given some insights into approaching that task.

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Can we predict the effects of artificial intelligence and virtual care on the health labour market?

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Abstract

Australian society, as is observed globally, is undergoing a profound demographic shift with an ageing population imposing increasing demands on the health system. There is a well-recognised association between an ageing population and the need for health and aged care. As such, the demand for high quality care services will grow necessitating the attraction, training and retention of workers supported by better use of technology and data. With increasing demand for a healthcare workforce of appropriate size and skill, attention has turned to new technologies such as artificial intelligence and virtual care as potential ways of dealing with labour market supply constraints. While these new technologies are exciting at this point, they are nascent and there is not, as yet, clear evidence that they will have a major effect on health workforce requirements. It is too early to be optimistic regarding artificial intelligence technologies in healthcare, and virtual care still requires a workforce to underpin its operations. Cautious evaluation is necessary before artificial intelligence and virtual care become practical in more complex human healthcare tasks or can emulate the abilities of humans in delivering human-centred healthcare.

JEL Codes: C45, I11, J01, J08, J23
Keywords: Healthcare; workforce; artificial intelligence; virtual care; modelling

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Introduction

At the beginning of the September of 2022, only four months after its election, the Albanese Government through the Department of the Treasury convened the *Jobs and Skills Summit* at Parliament House in Canberra. Although the remit of this meeting was wide ranging, among its key goals was to address skill shortages in the care economy. In particular, the issues document informing the summit referred to the following:

> "The most significant structural shift of the past 20 years has been the rise of the services sector. The growth in the health and care economy has been an important part of this trend. The healthcare and social assistance sector has more than doubled in size over the past 20 years, rising from 10 to 15 per cent of the workforce and now employs more than 2 million people… Labour shortages in the care workforce are already acute and expected to worsen with a projected shortfall of 286,000 care workers by 2050."[1]

In the lead-up to the summit the Minister for Health and Aged Care, Mark Butler MP, hosted a health workforce roundtable. Bringing together peak bodies from across the health and aged care sector, Minister Butler published remarks as follows:

> "Growing and supporting the health workforce is my priority – from nurses, to physios, to doctors, to cleaners, paramedics, wardies, security guards and every other health worker. We have an opportunity to invest in our current skilled workforce, and the skills of the next generation of health workers to better support their needs and deliver local jobs in communities across the country. My priority is to get this right to build the health workforce we need now and in the future."[2]

It should not surprise anybody that current demographic trends have underpinned a focus on the provision of healthcare: an ageing population – and therefore also an ageing workforce – with a greater prevalence of chronic and degenerative disease, requiring new patterns of more complex care and health technologies (Phillips, 2019). These demographic and health workforce pressures are being felt across the globe and are certainly not limited only to Australia or other high-income nations (Boniol *et al.*, 2022).

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1 Treasury Jobs and Skills: Report: https://treasury.gov.au/sites/default/files/inline-files/Jobs-and-Skills-Summit-Outcomes-Document.pdf

2 Mark Butler, August 2022: https://www.markbutler.net.au/news/media-releases/growing-and-supporting-our-health-workforce/

In the immediate aftermath of the summit then-chair of the Productivity Commission, Michael Brennan, delivered the Deeble Lecture in which he chose specifically to address the issue of health workforce and how technology might affect the delivery of healthcare:

> "Technology may … give the patient greater scope to take charge of their own healthcare needs, with a reduced role for an omnipresent healthcare worker. This approach means scarce healthcare workers can help more people, an outcome that is particularly valuable in regional and remote areas where labour shortages seem particularly severe. It also offers the potential to reduce burnout and stress on harried health workers and can promote better outcomes for patients."[3]

An adequate workforce is critical for the future sustainability of healthcare systems both in Australia and globally. As things stand, in the post-pandemic environment and with an ageing population demographic, there is likely to be a large gap between the care needs of the community and the healthcare workforce required to deal with them adequately (McPake *et al.*, 2024). In this paper we will explore the potential for two key technological 'solutions' – artificial intelligence (AI) and virtual care (VC) – to augment and increase the productivity of the healthcare workforce and, potentially, to take the place of healthcare workers. To do this we will review the roles and requirements of the healthcare workforce, explore the current and likely future capabilities of AI and VC to augment productivity and potentially take the place of healthcare workers, and draw on lessons from implementation of data-based 'solutions' in healthcare in the past.

People care for people

The delivery of healthcare is famously labour intensive, irrespective of the type of health system and its structural characteristics, levels, sources of funding, and even political underpinnings (Lee, Propper and Stoye, 2019). Ensuring an adequate workforce to provide healthcare is, thus, vital and an imbalance in supply of the necessary human resources delivering care can lead to severe economic and social harms, including life-long morbidity and preventable death (Amorim Lopes, Almeida and Almada-Lobo, 2015). Studies from health systems both in European countries (Hofmarcher, Festl and Bishop-Tarver, 2016) and the United States (Sheiner and Malinovskaya, 2016) have reported that healthcare workers are the most important resource in the care sector. While labour

3 The 2022 John Deeble Lecture is available here: https://ahha.asn.au/podcast/the-2022-john-deeble-lecture/

markets across industry and manufacturing have reported productivity gains resulting in job losses, this trend has not been observed in healthcare.

In Australia, increasing demand in the face of difficulties in recruitment and retention of healthcare workers – exacerbated by the COVID-19 pandemic – at the same time as international healthcare worker shortages are manifest have led to concerns about structural problems in the delivery of healthcare at entry, exit and follow-up from acute care (Looi *et al*., 2023). In a report for the US Brookings Institute, Sheiner and Malinovskaya (2016) concluded that productivity growth in the health sector has been much lower than economy wide productivity growth and possibly even negative. Those authors reflected a view that the healthcare industry is inherently incapable of achieving the same rates of productivity growth as the rest of the economy. Using historical evidence, they warned that the labour intensive nature of health care services makes health provider productivity unlikely to achieve improvement equal to the economy as a whole over sustained periods – mirroring Baumol's famous diagnosis of "cost disease" in service industries such as healthcare (Baumol, 1993).

In a situation of increasing demand for healthcare services, coupled with labour market constraints, it might be expected that technology improvements would lead to productivity gains. Surprisingly evidence to support this assumption is difficult to find. In a paper for the National Bureau of Economic Research (NBER), Bronsoler and colleagues (2021) examined the potential effects of information and communications technology – including clinical decision support systems – on the healthcare workforce. They found a relatively small literature dealing with the effects of these technologies on workers and, indeed, nothing to suggest that technology is reducing the need for healthcare workers such as nurses. Their overall conclusion was:

> "The literature points in a broadly optimistic direction in that the more recent cohort of studies suggests a positive effect on patient outcomes, but a more modest impact on productivity. Like the broader [information and communications technology] literature, this positive mean impact conceals a lot of heterogeneity underneath and long lags between adoption and outcomes, consistent with learning. Costs tend to rise, however, especially in the early adoption phase. The evidence on workforce outcomes is very slim, but what there is suggests little average effect with a hint of the heterogeneous effects by skill."

This finding – that the literature regarding the effects of technology on the healthcare labour market is scarce – has recently been echoed by other researchers (Borges do Nascimenta *et al*., 2023). Data from Australia show little evidence of a reduction in the healthcare workforce over periods of rapid technological change in the delivery of healthcare: the total number of Australians employed in healthcare has continued to increase (Figure 1). This increase has been associated with changes in the working hours of individual workers and the proportion working full time (Figure 2).

As the *Jobs and Skills Summit* highlighted, an appropriate health workforce is critical to the productivity to the country overall: unmet need in healthcare can have a direct negative effect on the economy (Suhrcke *et al*., 2009). There is strong evidence of a significant shortfall in the nursing workforce in Australia[4] and, at the time of writing, the Australian Government's *Nursing Workforce Strategy* was under review.[5] Medical practitioners are the group with the longest training time required to reach practice levels. The Australian Government released its *National Medical Workforce Strategy* in 2021[6] with the stated aim of guiding the "collective effort to ensure that our medical workforce meets Australia's ongoing health needs." Informing the Strategy are some key principles:

> "The medical workforce has a profound impact on the quality, accessibility, effectiveness and sustainability of the health system. However, inequality of access to health services remains a key issue for Australian communities. To achieve maximum benefit to the community, the medical workforce must be geographically well distributed and have the appropriate mix of medical specialties in each location. Currently this optimal distribution and service mix is not consistently achieved across Australia, resulting in service gaps and inefficiencies, and potentially impacting on the quality of patient care and the working life of Australia's doctors."

Of the five priorities articulated in the Strategy, priority number two is to rebalance supply and distribution of Australia's medical practitioners. This priority is underpinned by some key assumptions:

> "A key principle underlying Australia's healthcare system is that no individual or community group should be disadvantaged when accessing healthcare services. However, there are imbalances in Australia's medical workforce. There are undersupplied specialties, too few Aboriginal and Torres Strait Islander doctors, and poor distribution of doctors across the country, which leads to an over-reliance on locums and IMGs to service some areas. Growth in the subspecialist workforce and oversupply of some specialties has created training

4 Peters, M. (2023), 'Addressing nursing workforce shortages with comprehensive evidence-based strategies', *Australian Nursing and Midwifery Journal*. Accessible at: https://anmj.org.au/addressing-nursing-workforce-shortages-with-comprehensive-evidence-based-strategies/

5 National Nursing Workforce Strategy. Accessible at: https://www.health.gov.au/our-work/national-nursing-workforce-strategy

6 Commonwealth of Australia. National Medical Workforce Strategy 2021-2031. Accessible at: https://www.health.gov.au/sites/default/files/documents/2022/03/national-medical-workforce-strategy-2021-2031.pdf

> bottlenecks and risks supplier-induced demand and underemployment of new consultants."

As things stand there is a strong sense of impending crisis both within the medical profession (Skinner 2022) and the Australian community (Kirkham 2022).

The future of the future

Two new broad groups of technological advances – AI and VC – have received significant attention as potential ways to deal both with the demand for healthcare and constraints in the health labour market. These are related but have very different roles. The potential of AI has been addressed as follows by Aung and colleagues (2021), writing in the *British Medical Bulletin*:

> "Some of the most pressing current challenges facing healthcare are reduced expenditure, physician shortage and burnout, and the shift towards chronic disease management. As the workforce appears critically stretched, it has been proposed that AI, in particular deep learning, could be key to filling this gap. If AI systems are more widely adopted, not only could it reduce workload but also increase the quality of patient care."

What, exactly, is AI likely to be able to provide in a healthcare setting? A number of recent reviews have addressed this question in medical care (Alowais *et al.*, 2023), nursing care (Ruksakulpiwat *et al.*, 2024) and allied health areas such as physiotherapy (Shawli *et al.*, 2024). Alowais and colleagues (2023) summarise the key roles of AI as provision of assistance in decision making, workflow management, and 'timely task automation.' They provide a number of examples to illustrate these roles. Decision making is obviously important in healthcare and improvements in the accuracy of interpretation of very high volume tests such as x-rays, CT scans, blood tests, and tissue samples are welcome. However a physical worker is still required to take a blood specimen and process it. Similarly, a radiographer is required to position patients undergoing scans.

The medical imaging specialist must still review the images and provide a diagnosis, but AI systems have been demonstrated to reduce errors in making a diagnosis for patients. This has the potential to reduce further unnecessary tests and treatments for patients and improve efficiencies in laboratory work. It is possible that some diagnoses will be made earlier but those patients will likely need treatment anyway, so there may be an effect on the time at which treatment is provided.

Other examples are provided including streamlining of patient flow in emergency departments, reducing medication errors, and of expanding the role of 'precision medicine.' Again, each of these are important advances but how each would directly affect the need for healthcare workers remains unclear. One potential area is the use of 'AI-powered chatbots' that the review authors suggest may "help reduce the workload on healthcare providers, allowing them to focus on more complicated cases that require their expertise." Alowais and colleagues use the example of a smartphone app tested in the British National Health Service (NHS) that employed such chatbots as a potential alternative to telephoning a non-emergency number.

Ruksakulpiwat and colleagues' (2024) review of AI in nursing listed the major areas in which the technology was likely to change work patterns were in risk identification, medical record keeping, development of nursing care plans, and research. Similarly in physiotherapy, Shawli and colleagues (2024) review pointed to problem-solving, diagnostic decision making, and treatment planning as key roles for AI. In addition, the monitoring of rehabilitation and exercise programs at home using apps was another potential use of AI.

In all of the examples provided in comprehensive technology reviews, there are undoubtedly important and laudable outcomes. Improving safety in healthcare is important, as is not missing important diagnoses, good record-keeping, and the use of AI in analysis of large datasets to enable new breakthroughs in healthcare. There are also limitations of the AI deep neural networks used for healthcare and other applications, which will necessitate human intervention for the foreseeable future (Gigerenzer, 2022). Such AI systems function best in less ambiguous scenarios, such as in numerical computational tasks, whereas complex decision-making such as diagnoses based on history, investigation and physical examination have too many variables to contain (Gigerenzer, 2022). There are also two major fallacies, one from overfitting the algorithm so it precisely corresponds to the data and is ineffective as prediction; and the second, from the challenge of knowing what deep neural network has learned (Gigerenzer, 2022). Gigerenzer (2022, p.90) cites a research study of a deep neural network used to diagnose pneumonia from x-rays, that in fact used the rule of the use of a portable x-ray in the diagnosis, a rule ineffective for different situations in different hospitals. However, healthcare workers still will be required to take samples, move patients, operate on them, and take their x-rays, and due to the limitations of the AI, interpret investigations and examinations to make diagnoses, and plan treatments.

For these reasons the potential effects of AI technologies on the non-healthcare labour market have been difficult to foresee with some predicting that large numbers of jobs will be replaced, while others are much less pessimistic. A recent analysis and modelling by Shen and Zhang (2024) concluded that "the overall impact of AI on employment is positive, revealed a pronounced job creation effect, and the impact of automation technology on the labour market is mainly positively manifested as 'icing on the cake.'" This is a conclusion in line with that of other analyses and is based on AI technologies driving employment through capital deepening, division of labour, and increased productivity (Sharma and Mishra 2023; Feng *et al.*, 2024). Other reviews predict a more negative effect on the labour market. For example, Hatzius and colleagues' (2023) analysis concludes that:

> "The labour market could face significant disruption. Using data on occupational tasks in both the US and Europe, we find that roughly two-thirds of current jobs are exposed to some degree of AI automation, and that generative AI could substitute up to one-fourth of current work. Extrapolating our estimates globally suggests that generative AI could expose the equivalent of 300 million full-time jobs to automation."

The uncertainty in this debate within the healthcare literature reflects more fundamental conceptual questions about the nature of these digital health technologies and their relationships with labour. Are AI and VC *substitutes* for human health professionals, or are they *complements*? Are they therefore additive, improving outcomes by allowing human workers to do more (e.g. through improved diagnostic accuracy)? Or will they *replace* or *displace* human labour? Will they improve quality and clinical outcomes measurably, or will they drive increased low value utilisation through overdiagnosis and overtreatment (Hensher *et al.*, 2017)? The answers to these critical questions remain far from clear.

Agrawal and colleagues (2019) attribute this uncertainty to a fundamental misunderstanding of the role of AI in the labour market. In this context they treat AI as a prediction technology as separate and distinct from a decision mechanism:

> "Prediction is useful because it is an input into decision making. Prediction has no value in the absence of a decision. In this sense, each prediction task is a perfect complement to a decision task. A prediction specifies the confidence of a probability associated with an outcome under conditions of uncertainty. As an input into decision making under uncertainty, prediction is essential to many occupations, including service industries."

and, viewing it through that lens, posit four potential direct effects of AI on the labour market:

- The substitution of capital for labour in prediction tasks.
- Automation of decision tasks when automated prediction increases the relative returns to capital versus labour.
- Enhancing labour in the setting where automating the preceding prediction task increases labour productivity in subsequent decision tasks, thereby increasing the relative returns to labour versus capital in those tasks.
- Creation of new decision tasks when automating prediction sufficiently reduces uncertainty as to enable new decisions that were not feasible before.

Agrawal and colleagues (2019) use this framework to conclude that:

> "For any given worker, a key predictor of whether artificial intelligence will substitute for their job is the degree to which the core skill they bring to the job involves prediction… it is not yet possible to say whether the net impact on decision tasks – whether existing or new – is likely to favour labour or capital. We have found important examples of both, and there is no obvious reason for a particular bias to emerge. Thus, we caution on drawing broad inferences from the research on factory automation (for example, Acemoglu and Restrepo 2017; Autor and Salomons 2018) in forecasting the net near-term consequences of artificial intelligence for labour markets."

Combined with the limitations of the predominant deep neural networks (including AI large language models) due to the overfitting of algorithms masquerading as prediction, and the challenges of knowing whether the rules used to decide are generalisable and plausible to the real world (Gigerenzer, 2022), circumspection is warranted regarding the predictive prowess of AI. As discussed above, it may be that the AI can assist in parsing information to assist human physicians and healthcare workers in making complex decisions, for which deep neural networks are not suited due to the limitations of the technology.

Burnout and workforce retention are increasingly significant issues for the healthcare workforce and it is possible that AI could provide ways of alleviating these stressors, thus enhancing workforce retention (Hazarika, 2020). Yet Crawford (2021) points out a concerning – yet to her, a defining – feature of AI and automation:

> "AI technologies both require and create the conditions for ever more granular and precise mechanisms of temporal management. Coordinating time demands increasingly detailed information about what people are doing and how and when they do it."

There is a clear tension here with the culture of clinical autonomy in the service of the best interests of patients, that is fundamental to medicine. Indeed, Health and Montori (2023) question whether the pressures facing healthcare really are "…simply a crisis of organisation, efficiency, information, technology and scale." Perhaps, they suggest, the true crisis of care is precisely that we are imposing "technical" solutions instead of creating greater space for human-scale care to express itself.

It seems, then, that AI technologies are likely to lead to major improvements in the safety of patient care, in reaching accurate diagnoses earlier, in improving the efficiency of complex services such as pathology testing and medical imaging, and in 'personalised medicine.' These potential achievements are all to be applauded in keen anticipation. However, the vast majority of tasks in patient care will still require physical hands to provide and physician minds to decide – there is no getting around these facts. Even the most advanced robotic surgery still requires a surgeon to direct and a team of nurses to perform, with perhaps some reduced need for post-operative care elsewhere in a hospital (Maynou, McGuire and Serra-Sastre, 2024). In the case of non-urban healthcare settings, maybe AI-powered chatbots might reduce demand on primary care resources if triage worked and there were sufficient links to in-person services, there appears to be no evidence that workforce shortages in regional and rural areas can be addressed with AI.

Being there … or not – virtual care?

Virtual care (VC), in its most basic sense, is the provision of healthcare without the traditional physical contact – traditionally by using telephone or video platforms to conduct consultations with patients (Hardcastle and Ogbogu, 2020). However, rapid advances have extended the reach and resources to include not only electronic virtual visits but referral services, prescriptions, medical records, monitoring of physiological data such as blood pressure and blood sugar levels, digital therapeutics, care flow-ordered checklists, telepresence, and potentially even robotic surgery (Buyting *et al.*, 2021). The practical necessities of the COVID-19 pandemic have seen rapid uptake of VC and its expansion into areas where, previously, in-person contact was the almost invariable standard. Cancer care provides an example of such a domain and Singh and colleagues (2021) have undertaken a systematic review of the evidence pertaining to this particular clinical situation. They reported that the available evidence was somewhat limited, but that many aspects of cancer care could safely be provided virtually. Similar findings now have been reported for paediatric care (Goldbloom *et al.*, 2022) and mental healthcare. (Witteveen *et al.*, 2022).

There has been a long lead-in to the use of telehealth in mental healthcare in Australia, over 30 years, with pioneering of access to care in rural and remote regions, to specific incentivised provision of specialist psychiatric care in the same regions, through to expansion of partially subsidised specialist psychiatric care across metropolitan and rural regions during the COVID-19 pandemic (Woon *et al.*, 2024). Also in Australia, there has been substantial evidence of the uptake of telehealth for mental healthcare, both during and post-pandemic for a range of healthcare providers, including for psychological therapy (Reay *et al.*, 2021) and by medical specialists, such as psychiatrists (Looi *et al.*, 2022). However, there are particular patients and circumstances for which telehealth for mental healthcare is not suitable, and there remains no substitute for face-to-face provision of care in crisis, acute risk, or for those with disabilities and the aged (Looi and Pring, 2020). Notably, the provision of telehealth care still requires healthcare workers to deliver service via this medium.

A recent systematic review of VC in primary care and general practice – the lynchpins of medical care in the Australian health system – has concluded that "virtual consultations may be as effective as face-to-face care and have a potentially positive impact on the efficiency and timeliness of care; however, there is a considerable lack of evidence on the impacts on patient safety, equity, and patient-centeredness, highlighting areas where future research efforts should be devoted." (Campbell *et al*., 2023). There are challenges in the provision of virtual care, especially via telehealth, in that both the efficiency and fidelity to face-to-face consultation may be limited, especially for use of digital triage tools that may introduce unnecessary complexity and delays to the care process (Allison *et al*., 2024). The richness of virtual consultations can, potentially, be enhanced by incorporating monitoring and other technologies such as wearables that allow precise objective data to be available to health carers in real time (Mattison *et al*., 2022). The specific efficiency parameters of remote sensing for mental healthcare require further usability and validity research before regular clinical use (Bidargaddi *et al*., 2024). Economic analysis of telehealth and VC supports the use of telehealth and VC for subgroups of patients, for example those is rural areas of Australia, yet practitioners are still required to provide the consultations (Snoswell, North and Caffery, 2020). For this reason, distribution of the health workforce could be affected by a greater uptake of VC yet the overall size of the workforce might not be affected. Studies of VC in regional Queensland have demonstrated the safety of physiotherapy – traditionally associated with physical patient contact – in a VC setting, so prediction across the allied health workforce is likely to be difficult (Cottrell *et al*., 2021).

The need for an adequate skilled healthcare workforce in regional and rural areas of Australia may, in part, be reduced by the use of virtual care. However, in most cases this is an issue of distribution not of overall workforce requirement. VC – even if AI-assisted – will require healthcare workers to provide it from a remote location. VC will not alleviate the need for patients and their carers to travel to larger centres for physical care such as diagnostic testing and treatment, especially hospital based treatments.

Technologies in search…

Morozov has described the development of digital technologies driving a search for applications to human life as digital solutionism, rather than the converse approach wherein a need for a solution drives development of technology (Morozov, 2013). Furthermore, the context in which such digital and AI technological development occurs has been described by Zuboff as surveillance capitalism, wherein AI and other digital technology providers deliver products that both monitor users' behaviour and seek to encourage further monetisation through further use of the platform, and selling more products or services (Zuboff, 2019). AI and other digital health technologies, wielded judiciously and with careful targeting, can indeed play an important role in supporting a rejuvenated and rehumanised approach to health and aged care work and workers. But in its current form, AI – especially the explosion of LLMs in recent years – is more accurately described as an extractive and indiscriminate industry model (Crawford, 2021).

The actual process of clinical AI development displays many forces likely to drive applications towards sub-optimal real-world performance, and real risks of exacerbating inequities in health outcomes (Celi *et al.*, 2022). Meanwhile, the mechanisms by which clinical AI performs well (e.g. in image comprehension) remain opaque, with AI systems frequently offering incorrect rationales for correct image solutions (Jin *et al.*, 2024). Generative AI systems can also create false and/or misleading responses which are known as hallucinations and can have significant consequences in healthcare (Lee *et al.*, 2023). For example, a large language model generative AI used to assist in healthcare clinical note taking was described as creating a false Body Mass Index clinical measurement that was never included in the actual clinical interview (Lee *et al.*, 2023). Consequently, the use of AI technologies in healthcare can introduce further opportunity costs of loss of direct face-to-face care time from workers and from other clinical duties.

While, in theory, AI could additively impact the work of healthcare providers by reducing time spent performing administrative tasks – such as recording patient contact summaries – and increasing both the time taken, and accuracy of, diagnostic processes – the actual data for electronic health records and health information systems shows that administrative burdens are increased, leading to less patient care (Looi *et al.*, 2023). There could also be an impact on the demand side by enhancing remote patient monitoring and facilitating autonomous patient self-care, but the parameters require further calibration for effective interventions (Bidargaddi *et al.*, 2024). There could also be the potential for AI-assisted patient flow system improvements allowing more efficient resource allocation. Yet systematic reviews of the available evidence have highlighted the paucity of data to support these predictions (Wolff *et al.*, 2020). Indeed, it is possible that a requirement for a new category of healthcare workers skilled both in medical and data science might emerge. However, there is unfortunate evidence that electronic health information systems and records are not yet fit-for-purpose, in that they consume as much as a third of an extra day's work for healthcare workers to interact with and may detract from face-to-face patient care (Looi *et al.*, 2023). In Japan, after an effort lasting more than two decades to develop and introduce "care robots" into residential and home-based aged care settings, there is considerable evidence that the use of robots may require additional human oversight, which can actually detract from human care workers' ability to attend to clients directly (Wright, 2023). The corollary is that AI and virtual care must, like electronic health records, be optimally customised to assist healthcare workers in providing care more efficiently, rather than introducing more opportunity costs from struggling with the interfaces and functionality of this technology (Looi *et al.*, 2023). Furthermore, the administrative burden and opportunity cost of electronic health records has been a factor that can lead to healthcare worker burnout (Budd, 2023).

Summary

Australian society is undergoing a profound demographic shift with an ageing population imposing increasing demands on the health system (Harris and Sharma, 2018). This is a situation observed globally and is not unique to our country. There is a well-recognised association between an ageing population and the need for health and aged care, leading the Australian Productivity Commission, in its most recent *Intergenerational Report*, to note that "demand for high-quality care services is growing along with associated costs. Investing to attract, train and retain workers and skills will be crucial, supported by better use of technology and data."[7]

Workforce modelling in health is notoriously complex, (Lopes *et al*., 2015) and AI remains an area in healthcare in which expectation still frequently outweighs real achievements (Suran and Hswen, 2024). As our community faces an increasing demand for a healthcare workforce of appropriate size and skill, attention has turned to new technologies such as AI and VC as potential methods for dealing with labour market supply constraints. While these new technologies are exciting at this point, they are nascent and there is not, as yet, clear evidence that they will have a major effect on healthcare workforce requirements. This certainly has not been the case with technological developments to date. Indeed, it seems possible that the introduction and administration of new technologies such as AI and VC might actually increase the need for healthcare-associated workers, or they could increase training times required for practice proficiency. And, unfortunately, if AI technologies are not fit-for-purpose, they may negatively impact the temporal and clinical efficiency of healthcare workers who have to check that the outputs and actions are safe and effective to improve patient care. There certainly is potential for extending care to populations in rural and remote areas, where workforce shortages are most acute, and also possibly to groups at special disadvantage. It is too early to be optimistic regarding AI technologies in healthcare. Cautious evaluation is necessary before AI use is practical in more complex, human healthcare tasks, or can emulate the abilities of humans in delivering human-centred healthcare.

> *"Perhaps. But we cannot reckon with what is lost when we start out to transform the world."*
>
> Karel Čapek, R.U.R.

7 Australian Government: Intergenerational Report 2023. Accessible at: https://treasury.gov.au/sites/default/files/2023-08/p2023-435150.pdf

Figure 1. Trends in the healthcare workforce (ABS)[8]

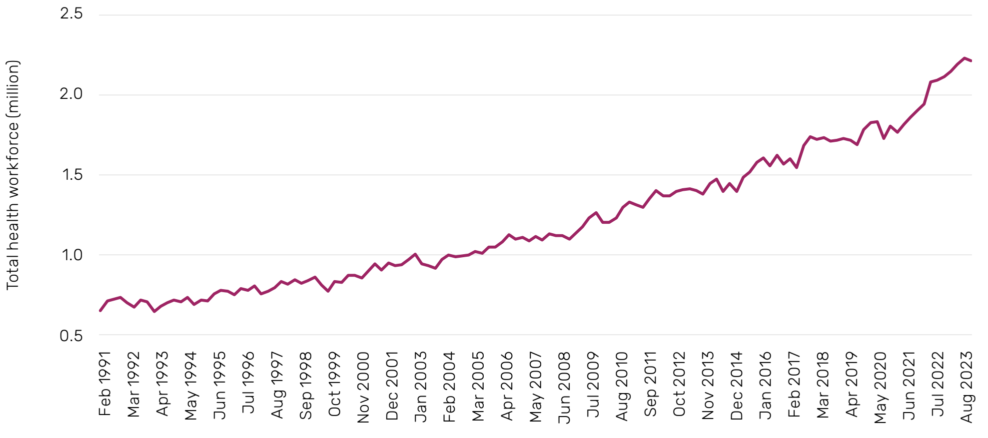
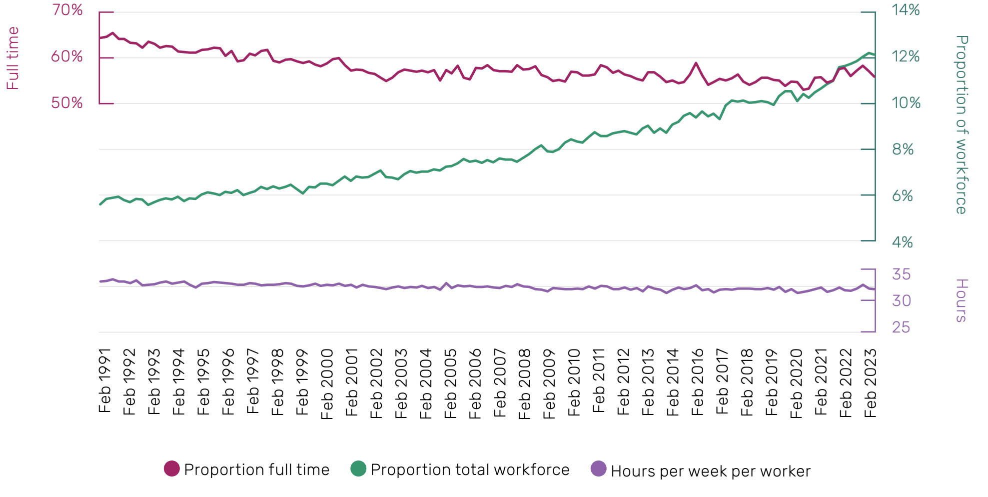


Figure 2. Trends in healthcare workforce characteristics. The proportion of the workforce employed full time (top), the health workforce as a proportion of the total Australian workforce (middle), and the mean weekly hours worked by Australian healthcare workers (ABS)



8 https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release#data-downloads

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Unemployment entry, exit and Okun's law: An analysis with Australian data

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Abstract

This paper sets out a new approach to understanding Okun's law and the evolution of the unemployment rate in Australia. Okun's law can be expressed in terms of a relationship between first differences in the unemployment rate and the growth rate of real GDP while changes in the unemployment rate in turn can be expressed in terms of flows into and out of unemployment. Having established that Australian data is consistent with the 'change' version of Okun's Law we then examine the unemployment entry and exit rates to determine the extent to which the variations in one or both of these rates can be explained by variations in GDP growth. It would appear that the asymmetry in the relationship reflects a greater impact of changes in GDP growth on the entry rate and not the exit rate.

Keywords: Labour market flows; Okun's law; Equilibrium unemployment rate; Australia
JEL Codes: J640; E240; E320

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Introduction

In this paper we present a new approach to understanding the Okun relationship for Australia. Specifically, we aim to examine variations in the rates of entry into and exits from unemployment to determine the extent to which variations in one or both of these rates can be explained by variations in GDP growth. We are especially interested in identifying which flows are the source of the asymmetry in the relationship between GDP growth and changes in the unemployment rate.

Okun's law is commonly expressed in terms of a relationship between deviations from trend in the unemployment rate and deviations from trend in the level of real GDP, or alternatively, in terms of a relationship between first differences in the unemployment rate and the growth rate of real GDP. In this paper we examine the second version of Okun's law. This is because it is changes in the unemployment rate that can be expressed in terms of unemployment entry and exit and so it is the change version of Okun 's law that leads directly to an examination of the relationship between unemployment entry and exit rates on the one hand and GDP growth on the other. While logic dictates that the Okun relationship must reflect the impact of changes in the rate of economic growth on flows into and/or out of unemployment we cannot say a priori whether it is one or both of the flows which react to changes in the growth rate or know the direction and relative size of the reactions. These are issues that can only be addressed empirically.

The structure of the paper and some of the important conclusions reached in each section are as follows:

In section 2 we examine the relationship between changes in the unemployment rate and the rate of economic growth. After a very brief literature survey we estimate a 'change' version of Okun's law using Australian data over the period 1979Q4 – 2023Q4. Amongst other things, we show that we can reject the hypothesis that variations in the growth rate do not Ganger cause variations in the unemployment rate. We also see that there is asymmetry in the relationship such that the extent of the change in the unemployment rate which results from a change in the rate of economic growth varies depending upon whether the economy is in a recession period (which we define as a period when quarterly growth rates are below the trend growth rate) or not. As mentioned above one of the aims of this paper is to determine the 'source' of the asymmetry using data on unemployment inflow and outflow.

Key elements of the relationship between the unemployment rate and flows into and out of unemployment are presented in Section 3. We find (as do others who research in this area) that inflow and outflow are cointegrated with a cointegrating vector of (1, -1), implying that, if there is a 'step' increase in inflow, sooner or later the outflow will rise by an amount equal to the rise in the inflow. We then examine the flow from unemployment to employment and show that, strange as it may seem, more unemployed people find jobs in recessions than in booms and we explain why this is so. In section 4 of the paper we examine the relationship between the unemployment entry and exit rates and the equilibrium unemployment rate and also the relationship between the equilibrium unemployment rate and the actual unemployment rate. We show that there is a very close relationship between these two rates such that the equilibrium rate of unemployment (and this the relative size of the entry and exit rates) is a very good predictor of the actual rate of unemployment and we show why this is so.

In section 2 of the paper we establish that there is a relationship between changes in the unemployment rate and GDP growth while in sections 3 and 4 of the paper, we show that changes in the unemployment rate reflect the relative size of flows into and out of the unemployment 'pool'. Clearly, taken together, these findings imply that there must be an empirical relationship between GDP growth and one or both of the flows in to and out of unemployment. We examine this in section 5 using Vector AutoRegression (VAR). While both entry and exit rates respond to variations in the GDP growth rate, we find that the presence of asymmetry in the relationship is a reflection of the way in which entry into unemployment responds to changes in the growth rate and that it does not appear to reflect the responsiveness of exits from unemployment to changes in the growth rate.

In the following section of the paper we begin our analysis by looking at recent evidence for the 'change' version of Okun's Law for Australia, that is, evidence for a relationship between the change in the unemployment rate and GDP growth. In all of our empirical work we use Australian data over the period 1979Q4 – 2023Q4 downloaded from the ABS website.[1]

The 'changes version' of Okun's Law

Since our ultimate aim is to examine the relationship between unemployment entry and exit rates and GDP growth in order to throw light on the 'Okun' relationship between the change in unemployment and GDP growth (Okun, 1962), it is necessary for us to first establish that there actually is a relationship between the change in the unemployment rate and GDP growth.

An important aside: In what follows we refer to the coefficient measuring the effect of a change in the GDP growth rate on the change in the unemployment rate (or on unemployment entry and exit rates) as "the Okun coefficient".

1 Quarterly real GDP data are taken from the *Australian National Accounts: National Income, Expenditure and Product* releases. Labour force measures such as the unemployment rate and flows in to and out of unemployment are taken from *Labour Force, Australia* releases. The monthly gross flows have been made stock consistent. For an explanation of the method used and the reasons why it is important to use stockconsistent figures see Frazis *et al.* (2005) and Dixon *et al.* (2007). The flows data are seasonally adjusted using Census X13 and the quarterly observations are averages of the monthly flows.

Research undertaken by Guisinger and Sinclair (2015)[2], Valadkhani (2015)[3] and Ball *et al.* (2017[4] and 2019[5]) suggests that there is such a relationship for Australia. Since none of these studies could be said to be using 'recent' data we begin by examining the empirical relationship between GDP growth and changes in the unemployment rate for persons in Australia over the period 1979:4 – 2023:4. We use the 'quarter on quarter before' as our measure of change (rather than (say) annual changes or comparing each quarter with the value for four quarters before) as changes in unemployment and in the flows in the labour market, especially in recessions, can occur quickly and turning points eg trough to peak unemployment can occur in a period less than a year.

The first two data columns in Table 1 report descriptive statistics for the first differences in the unemployment rate and the GDP growth rate. Amongst other things, we see that both variables are I(0).

2 Guisinger and Sinclair (2015) estimate an equation where the annual change in the unemployment rate is regressed on the annual growth rate of GDP (no lags are included and there is no allowance for asymmetry). The data set covers the years 1989 – 2011. Australia is one of the countries they examine. They find a statistically significant Okun coefficient of -0.50.

3 Valadkhani (2015) estimates a number of models of Okun's law involving four-quarter changes in the variables. The sample period is 1980Q3 – 2014Q1. In a model with a fixed coefficient and with lags at -1, -4, -5 and -6, the estimated short-run value of the Okun coefficient is -0.131 while the long-run value is estimated to be -0.420. The author also tests for asymmetry in the Okun coefficient and finds that the coefficient becomes more negative in recessions.

4 Ball *et al.* (2017, p. 1439) write that Okun's law "… is strong and stable by the standards of macroeconomics". Australia is one of the countries they examine. For quarterly data over the period 1980Q1 – 2013Q4 they find an Okun coefficient of -0.410.

5 Ball *et al.* (2019, p 856) find an Okun coefficient of -0.508 for annual data for Australia over the period 1980-2015.

Table 1. Descriptive Statistics (quarterly averages of monthly seasonally adjusted data): 1979:4 – 2023:4 (%) – First-differences and the GDP growth rate

	ΔUnemployment rate	GDP growth rate	Δln (Entry rate)	Δln (Exit rate)
Mean	-0.0131	0.7461	-0.00178	0.00072
Std. deviation	0.3311	1.0095	0.05913	0.04117
Unit Root test (ADF) p-value*	-7.1800 0.0000	-12.8215 0.0000	-14.4270 0.0000	-15.8124 0.0000
Contemporaneous Correlations				
ΔUnemployment rate	1.000			
GDP growth rate	-0.475	1.000		
Δln (Entry rate)	0.666	-0.465	1.000	
Δln (Exit rate)	-0.477	0.084	0.096	1.000

* The null is that the variable has a unit root.

The results of a simple OLS regression with (seasonally adjusted) quarterly data for the period 1980Q4 – 2023Q4 of the quarter on the quarter before change in the unemployment rate as the dependent variable on (i) the quarter on the quarter before growth rate of real GDP, (ii) a slope dummy to test for asymmetry in relation to recession periods[6] and (iii) the lagged change in the unemployment rate, are given in the first 'data' column of Table 2 below.[7]

As expected we find that there is a negative relationship between the change in the unemployment rate and GDP growth.[8] It would also seem that there is asymmetry in the relationship and specifically that the Okun coefficient is more negative in recessions (which we define as periods of negative deviations of the actual growth rate from the Hodrick-Prescott trend growth rate) than it is in other periods. The long run value of the Okun coefficient outside of recessions is estimated to be -0.183 while in recessions the long run value is estimated to be -0.434.

6 We test for this by using a slope dummy which is 1 when there is a negative deviation of the rate of GDP growth from the Hodrick-Prescott trend in GDP growth rates (quarter on quarter before) and 0 in all other periods.

7 If a shift recession dummy is included in the equation the p-value on the coefficient is 0.3685. As a result we drop the shift dummy but retain the slope dummy.

8 Granger causality tests indicate that we cannot reject the null that changes in the unemployment rate do not Granger cause the GDP growth rate while we can reject the null that the growth rate does not Granger cause changes in the unemployment rate.

Table 2. Estimated coefficients (p-values in parentheses)

Estimation method	OLS (HAC)*	VAR	
Dependent variable	Δ*UR*	Δln (*en*)	Δln (*ex*)
C	0.0751 (0.0083)	0.0127 (0.0070)	-0.0042 (0.2034)
GDP growth rate	-0.0936 (0.0017)	-0.0156 (0.0005)	0.0062 (0.0491)
Slope dummy for Recessions	-0.1286 (0.0001)	-0.0359 (0.0000)	-0.0070 (0.3120)
Lagged dependent variable	0.4880 (0.0000)	–	–
Number of lags on the variable in the VAR	–	5	5

* OLS (HAC) is Heteroskedasticity and Autocorrelation Consistent (Newey-West) estimation.

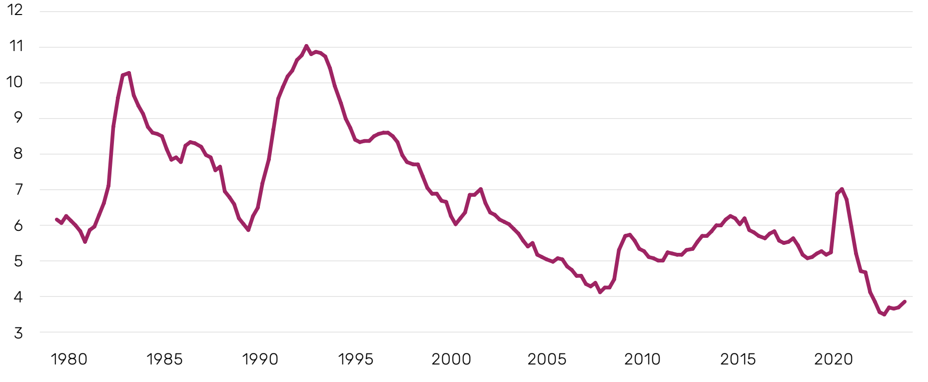
To summarise: there is a good deal of evidence for Australian data covering different periods that the 'change version' of Okun's Law is a reasonable description of variations in the unemployment rate in Australia. In what follows we will take this as 'a given'. Now, clearly the change in the unemployment rate reflects the balance of flows into and out of unemployment within any period and so it is natural to look at the Okun relationship as 'merely' being the refection of a relationship between output growth and one or more labour market flows. The justification for focusing on the flows is that we will see in the sections which follow: (i) that the actual rate of unemployment follows the (stochastic) equilibrium rate very closely (and we will also see why this is), (ii) that movements in the equilibrium rate depend upon movements in the entry and/or exit rates and, (iii) since the unemployment rate varies with the GDP growth rate it follows that one or both of the entry and exit rates must be varying with the growth rate of real GDP.

In the next section of the paper we examine the relationship between changes in the unemployment rate and flows into and out of unemployment.

Dynamics of Unemployment: Inflow and Outflow[9]

The main characteristics of the evolution of the unemployment rate are depicted in Figure 1 which shows quarterly averages of seasonally adjusted monthly values for the unemployment rate for persons over the period 1979Q4 – 2023Q4. Notable are the two 'major' recession episodes of 1981-1983 and 1990-1993 together with increasing unemployment following the GFC in 2008-2009 and the COVID-19 related rise in 2020. We also see the long, slow, recovery from the recession of the early nineties and the sharp fall in unemployment following the lifting of the COVID-19 restrictions.

Figure 1. Time Series of Unemployment Rate for persons (seasonally adjusted) (%): 1979:4 – 2023:4



The unemployment rate is defined as the ratio of the number unemployed (*U*) to the total labour force (*LF*). Allowing for both *U* and *LF* to vary over time, the change in the unemployment rate (*UR*) can be expressed as:[10]

$$\Delta(UR_t) = \frac{U_t}{LF_t} - \frac{U_{t-1}}{LF_{t-1}} = \frac{\Delta U_t}{LF_t} - \left(\frac{U_{t-1}}{LF_t}\right)\left(\frac{\Delta LF_t}{LF_{t-1}}\right) \tag{1}$$

9 This section draws upon Dixon *et al*. (2007).

10 We are using monthly flows data based on matched records. Here, the subscript 't-1' on a stock variable refers to its value at the beginning of the month while the subscript 't' refers to its value at the end of the month. For a flow variable the subscript 't' refers to the flow during the month while the subscript 't-1' refers to the flow during the previous month.

where Δ represents a discrete change operator.

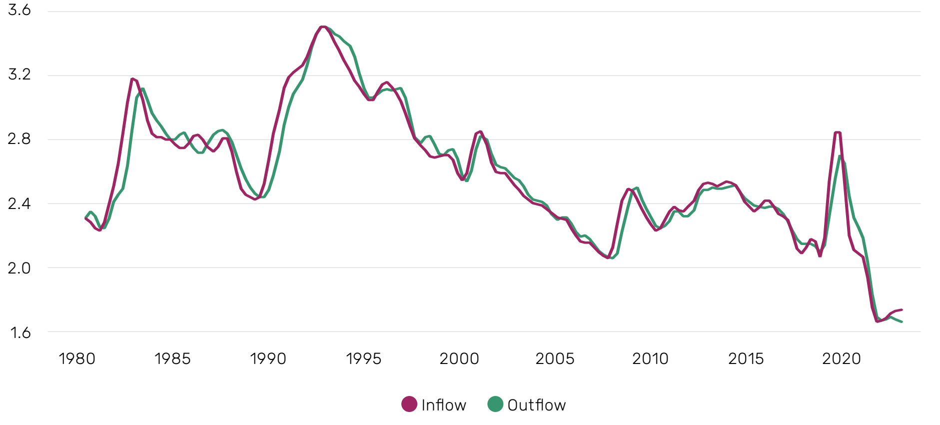
Changes in the number unemployed over time (Δ*U*) reflect the balance between two flows, an inflow into unemployment (*IN*) and an outflow from unemployment (*OUT*). Given this equation (1) may be written as:

$$\Delta(UR_t) = \frac{(IN_t - OUT_t) - U_{t-1}\left(\Delta LF_t / LF_{t-1}\right)}{LF_t} \tag{2}$$

Since the change in the labour force over a 'short' discrete period, like a month, is likely to be small,[11] it follows that both Δ*LF/LF* and especially $(U_{t-1} / LF_t)\,(\Delta LF_t / LF_{t-1})$ are likely to be quite small (both in absolute terms as well as relative to the other component in the equation), hence we will follow other researchers and throughout treat

$$\Delta\left(UR_t\right) \approx \left(\Delta U_t / LF_t\right) = (IN_t - OUT_t)/LF_t \tag{3}$$

Figure 2. Unemployment Inflow (blue line) and Outflow (brown line) rates as a percentage of the labour force (seasonally adjusted and smoothed data): 1980:3-2023:4



11 The average monthly values of the relevant variables expressed as percentages of the labour force are: *IN/LF* = 2.572%, *OUT/LF* = 2.577%, Δ*LF/LF* = 0.052% and (*U/LF*)*(Δ*LF/LF*) = 0.004%.

The evolution of inflow and outflow rates over time in Australia is depicted in the two inter-twined series in Figure 2.[12] The inflow rate (*INR*) is defined as the sum of the flows from employment and from not in the labour force into unemployment over the month expressed as a proportion of the labour force (ie *INR* = *IN/LF*). The outflow rate (*OUTR*) is defined as the sum of the flows from unemployment to employment and to not in the labour force over the month, also expressed as a proportion of the labour force (ie *OUTR* = *OUT/LF*). Granger causality tests show that while we cannot reject the hypothesis that *OUTR* does not Granger cause *INR*, we can reject the hypothesis that INR does not Granger cause OUTR. Tests show that *INR* and *OUTR* are both I(1). Fitting a Vector Error Correction model to the two series we find that INR is exogenous[13] and that the two series are cointegrated with a cointegrating vector of approximately (1, -1), implying that, if, following a sustained exogenous shock, the inflow rate increases, sooner or later, the outflow rate will rise by an amount equal to the rise in the inflow rate. This is not a feature of Australian data alone – Balakrishnan and Michelacci (2001) find that Inflow and Outflow Rates for the US, UK, Germany, France and Spain also have cointegrating vectors of (1, -1). Yashiv (2007) looked at a number of US data sets and found that "job finding and separation into unemployment move together along a 45-degree line" (p 796).[14]

An implication of our finding that *INR* and *OUTR* are cointegrated with a cointegrating vector of approximately (1, -1) is that, paradoxically as it would seem, we would expect to observe that more unemployed people find jobs in a recession than in

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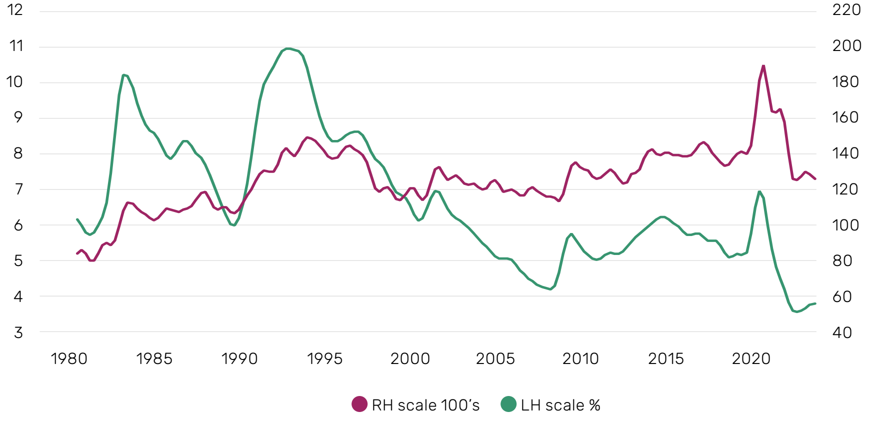
12 So as to better display the underlying movement, the series depicted in Figures 2–5 are based on quarterly averages of monthly rates which have been seasonally adjusted and smoothed using a 7-period Henderson moving average (see Henderson (1916) and Gray and Thomson (1996) for a description). This is because monthly and quarterly flows data, even when seasonally adjusted, is very noisy. In the statistical and econometric work which underpins results reported in this paper we use seasonally adjusted, but not smoothed, quarterly averages of monthly data. In all of our econometric work we use the Akaike information criterion (AIC) to determine the number of lags to include in the model. EViews is used throughout.

13 This result is not surprising. Balakrishnan and Michelacci (2001) find the same for the US, UK, Germany, France and Spain over the period 1972:3 – 1989:4. Burgess and Turon (2005, p 433) also find this for UK claimant count data over the period 1967:1 – 1998:4 while Dixon and Mahmood (2006) find that this is also true for UK claimant count data over the period 1989:1 – 2003:4. Fujita and Ramey (2009) find this for US data over the period 1976:1 – 2005:4 while Bryson (2024) finds this for US data for the period 1979:4 – 2019:4. Elsby *et al*. (2013) find this for fourteen OECD countries (and they also draw attention on p 544 to a number of earlier papers using US data who have also found this). It should be noted that they conclude that "these findings for worker flows are a *stylized fact* of modern labor markets" (p 547, our emphasis).

14 This relationship was also reported for Australian data over the period 1979Q3 – 2007Q3 by Dixon *et al*. (2007, p 209) and for UK data by Burgess and Turon (2005, p 440).

a boom![15] (We would also expect to observe that more unemployed people move out of the labour force in a recession than in a boom and this is indeed the case, but unlike our finding for the number moving from unemployment to employment, this is not surprising.) Figure 3 shows the unemployment rate (as a percentage) and also the number of people (in thousands) who were classified as unemployed at the beginning of each month but who were classified as employed at the end of the month.[16] Clearly, while the job finding probability might fall in a recession, the expansion in the number unemployed more than offsets this with the result that the absolute number of unemployed finding employment increases during recession episodes. Burgess and Turon (2005) argue that one of the factors responsible for the induced rise in outflow is related to hirer's preference for people who have not been unemployed for long periods. They assume that the probability that an individual will receive a job offer "declines over duration [and, as a result of this,] the average measured outflow rate depends on the duration structure of the unemployment stock and this, in turn, depends on the movement in the inflow. As the economy turns down, more people flow in, the ratio of newly unemployed increases and hence so does the average outflow rate" (p 437f).

Figure 3. The flow from unemployment to employment and the unemployment rate, seasonally adjusted and smoothed data: 1980:3-2023:4



15 See Dixon *et al*. (2007, passim), Borland (2009, p 238f) and Evans (2018, p 478f) for both a demonstration and a more extensive discussion of this in the context of Australian data. Mercan *et al*. (2024) find that "the fact holds across OECD countries" (p 245 and Appendix A.5). It has also been documented in papers by Blanchard and Diamond (1990), Burda and Wyplosz (1994), Fujita and Ramey (2009) and Elsby *et al*. (2013).

16 Recall that we are working with quarterly averages of monthly figures.

A parsimonious model of unemployment rate equilibrium and short-run dynamics

Although flows between three labour market states – employed, unemployed and 'not in the labour force' – are involved when modelling changes in unemployment, it is common in the literature to model unemployment dynamics in a parsimonious fashion with the aid of only a single entry rate to unemployment and a single exit rate from unemployment.

By definition:

$$\Delta U_t = \left(\frac{IN_t}{E_{t-1}}\right)E_{t-1} - \left(\frac{OUT_t}{U_{t-1}}\right)U_{t-1} = en_t E_{t-1} - ex_t U_{t-1} \tag{4}$$

where *en* is the "entry rate" into unemployment defined as *en(=IN/E)* and *ex* is the "exit rate" from unemployment defined as *ex(=OUT/U); E* is the total number employed and *U* is the total number unemployed. Notice that *en* includes flows from both employment and not-in-the-labour force to unemployment while *ex* includes flows from unemployment to both employment and not-in-the-labour force.

Dividing both sides of (4) by the labour force *(LF = E + U)* yields an expression for the evolution over time of the unemployment rate:

$$UR_t - UR_{t-1} \approx \frac{\Delta U_t}{LF_{t-1}} = en_t - \left(en_t + ex_t\right)UR_{t-1} \tag{5}$$

As we shall see the data in the 'levels' are not stationary, and so it is not particularly meaningful to compute a single 'natural' or 'equilibrium' rate as clearly there is no meanreversion behaviour.[17] Instead, we propose to work with a time-varying 'equilibrium unemployment rate'. Given (5), the unemployment rate associated with 'flow equilibrium' (in the sense of $\Delta U_t = 0 \; \forall \, t$), or what Hall calls the "stochastic equilibrium unemployment rate" (UR^*_t) will be:[18]

$$UR^*_t = \frac{en_t}{en_t + ex_t} = \frac{1}{1 + \left(ex_t / en_t\right)} \tag{6}$$

The main advantage of this framework is that we can study the behaviour of an unobservable variable (the equilibrium rate of unemployment) by studying the behaviour

17 I am grateful to Guay Lim for pointing this out to me.

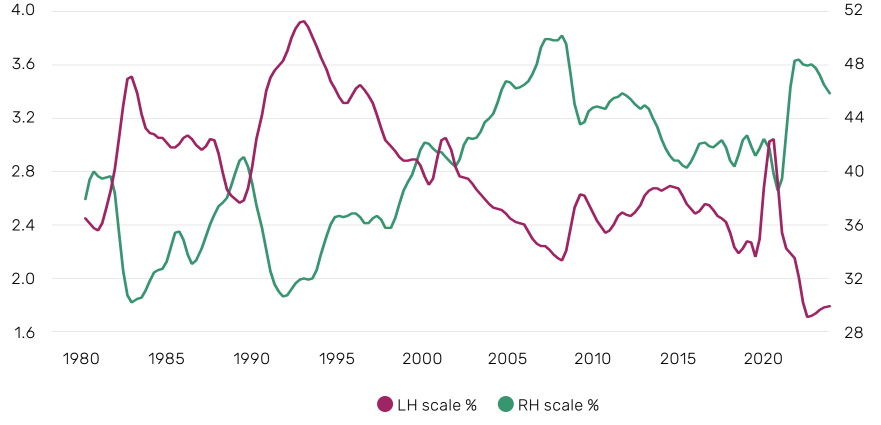
18 See Hall (2003, p 147f and 2005, p 398f). Hall also uses the term "stochastic stationary state". Elsby and Smith (2010, p R32) use the term "flow steady state value" for this concept while Mercan *et al.* (2024, p242) use the term "steady state unemployment rate".

of observed variables (entry and exit rates). Fortunately, as we shall see, the dynamics of the actual rate around the equilibrium rate also depends upon *en* and *ex*.

Figure 4 shows the evolution of the entry (*en*) and exit (*ex*) rates over the period 1979:4- 2023:4.[19] Both rates are highly variable but are clearly inversely related.[20] The entry to unemployment rate, *en*, rose sharply in the recessions of 1981-83 and 1990-92 and then fell slowly in the period between the two. It rose at the time of the GFC and also at the time of the pandemic-related lockdowns in 2020. The exit from unemployment rate, *ex*, fell during the recession periods and increased during the recovery phases following the two recessions and also as restrictions were eased towards the end of the pandemic.[21]

Table 3 presents some descriptive statistics for the levels of the entry and exit rates and the unemployment rate. Not surprisingly, the unemployment rate is positively correlated with the entry rate and is negatively correlated with the exit rate. We also see that the exit rate is negatively correlated with the entry rate. Notice, in passing, that all of these variables in 'the levels' are I(1).[22]

Figure 4. Entry and Exit Rates (seasonally adjusted and smoothed data): 1980:3-2023:4



19 Again, we have plotted the seasonally adjusted (and smoothed) entry and exit rates and again, the numbers are quarterly averages of monthly data.

20 As will be seen in Table 3 the contemporaneous correlation coefficient between the two is -0.815.

21 Other authors observe similar cyclical variations in the entry and exit rates as we find here – see for example Burgess and Turon (2005) and Elsby and Smith (2010).

22 The first differences of all of the variables is, as expected, I(0).

Table 3. Descriptive Statistics (quarterly averages of monthly seasonally adjusted data): 1979:4 – 2023:4 - Levels

	Entry rate (%)	*Exit rate* (%)	*Unemployment rate* (%)
Mean	2.765	40.089	6.642
Std. deviation	0.484	5.195	1.830
Unit Root test (ADF) p-value*	-1.915 0.325	-1.604 0.478	-2.005 0.285
Contemporaneous Correlations			
Entry rate	1.000		
Exit rate	-0.815	1.000	
Unemployment rate	0.954	-0.928	1.000

* The null is that the variable has a unit root.

Insights about the dynamics of the observed unemployment rate can be obtained by combining (6) and (5) to give a partial adjustment model:

$$UR_t - UR_{t-1} = \left(en_t + ex_t\right)\left(UR^* - UR_{t-1}\right) \tag{7}$$

Equation (7) shows that the higher is ($en + ex$) the faster is the adjustment in the event of any disequilibrium. Amongst other things, this shows that the determinants of the equilibrium rate and the determinants of the short-run dynamics, and especially the 'persistence' of the unemployment rate, are interrelated. In particular, changes in the equilibrium rate are *necessarily* accompanied by changes in the rate of adjustment and thus in persistence.

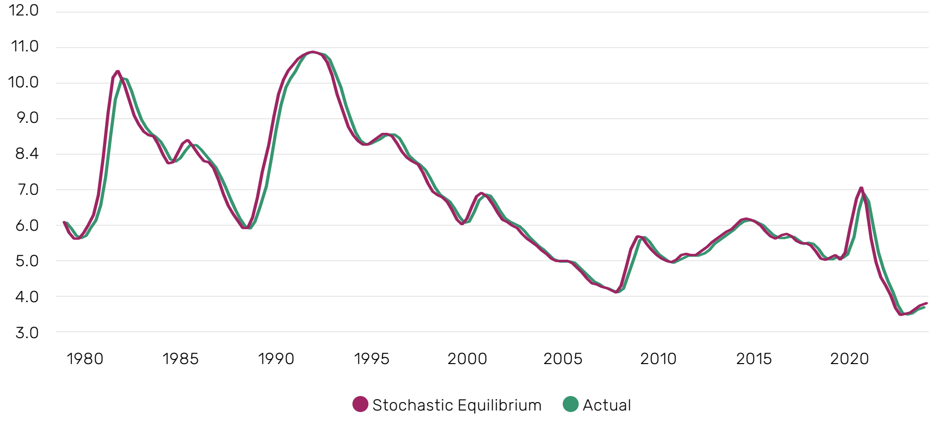
Figure 5 compares the stochastic equilibrium unemployment rate UR^*_t (computed using equation (6) and the observed values of en_t and ex_t in each period) with the observed unemployment rate.[23] The two series are clearly closely related with a contemporaneous correlation coefficient of 0.995. It is also clear that the equilibrium rate leads the actual rate.[24] The mean absolute deviation of the observed unemployment rate from the equilibrium rate is 0.126 per cent, which is very small when compared with

23 In Figure 5 we display seasonally adjusted and smoothed rates. The correlation coefficient and the measures of the difference between the equilibrium and actual rates are computed using seasonally adjusted but not smoothed entry and exit rates.

24 And so the equilibrium rate might be useful for forecasting, see Barnichon and Nekarda (2012).

the mean value of the observed unemployment rate of 6.643 per cent. As Hall (2005, p 398), Burgess and Turon (2005, p 430), Petrongolo and Pissarides (2008, p 257f), Fujita and Ramey (2009, p 88), Shimer (2012, p 132) and others have noted, the close correlation between the actual and stochastic equilibrium rate suggests that it may be safe when modelling unemployment, to initially neglect 'turnover dynamics' and focus on the stochastic equilibrium rate and its determinants.

Figure 5. Actual and Stochastic Equilibrium Unemployment Rates (seasonally adjusted and smoothed data) 1980:3-2023:4



To see why the stochastic equilibrium and actual unemployment rates are closely related we rearrange (7) to obtain an expression for the gap between the observed rate of unemployment and the equilibrium rate. It is:

$$UR_t - UR_t^* = \left(en_t + ex_t - 1\right)\left(\frac{en_t}{en_t + ex_t} - UR_{t-1}\right) \tag{8}$$

It follows that if ($en_t + ex_t$) is high and/or shocks to *en* and *ex* are small, the actual unemployment rate in any period would be close to the stochastic equilibrium rate. In fact, the average value of ($en + ex$) is 43 per cent per month implying that on average around 82 per cent of the adjustment will take place within one quarter.

In relation to the dynamics of the system, we have already noted the rate of adjustment of the observed unemployment rate to the equilibrium rate is given by *the sum* of *en* and *ex*. For our data set the value of the sum of *en* and *ex* is (as we would expect) negatively correlated with both the observed unemployment rate and with the stochastic equilibrium rate (UR*), with correlation coefficients of -0.906 and -0.905

respectively. This implies that if the (equilibrium) unemployment rate is low the speed of adjustment will be high, and vice-versa.

We have seen the role of the entry and exit rates in determining the stochastic equilibrium unemployment rate and we have also seen that the actual unemployment rates follows closely movements in the (stochastic) equilibrium rate. Our most fundamental proposition in this paper is that, if there is a relationship between the growth of real GDP on the one hand and changes in the unemployment rate on the other (as set out in Okun's law), then there must be a relationship between the growth of real GDP on the one hand and changes in one or both of the rates at which people flow into and out of unemployment on the other. Whether it is one or both of the rates is an empirical question and cannot be determined a priori.

The relationship between changes in the entry and exit rates and GDP growth

In this section of the paper we focus on to the relationship between changes in the unemployment entry and exit rates and GDP growth.[25] We are especially interested (inter alia) in these questions: (i) What is the relationship between variations in the entry and exit rates and GDP growth? and (ii) What appears to be the source of the asymmetry in the Okun relationship? Is it the entry rate, the exit rate or both?

Before proceeding any further, we note that the unemployment rate (*UR*) and the ratio of the number unemployed to the number employed (*U/E*) are monotonically related. By definition:

$$UR = \frac{U}{LF} = \frac{1}{1+\left(E/U\right)} = \frac{1}{1+\left(1/\left(U/E\right)\right)} \tag{9}$$

which implies that we can explain the behaviour of the unemployment rate by explaining the behaviour of the ratio of the number unemployed to the number employed (and vice versa). As in the earlier case, if we had flows equilibrium at the prevailing entry and exit rates, that is inflow ($en \times E$) equals outflow ($ex \times U$), we can solve for the 'stochastic equilibrium' ratio of the number unemployed to the number employed at any moment in time:

25 Lim *et al*. (2021) also takes a 'flows approach' to Okun's law but that paper uses US data and the focus is on the relationship between changes in GDP and the *net flows* between *all* labour market states and not on the relationship between changes in GDP and the unemployment entry and exit rates.

$$\left(U/E\right)_t^* = \frac{en_t}{ex_t} \tag{10}$$

which is to say that movements in the ratio of unemployment to employment (and thus movements in the ratio of unemployment to the labour force) reflect *relative* levels of the entry and exit rates including the impact of a shock to GDP growth on the relative proportionate changes in the entry and exit rates. The advantage of looking at the ratio of the number unemployed to the number employed (*U/E*), rather than the unemployment rate (*U/LF*) is that, while the equilibrium unemployment rate is related in a non-linear fashion to the entry and exit rates, equation (10) implies that there will be a simple linear relationship between the logarithm of the ratio of unemployment to employment in any period and the logarithms of the entry and exit rates and the same may be said the of the logarithms of the first-differences. For convenience of exposition, we call the RHS of equation (10) the 'stochastic equilibrium unemployment ratio' to distinguish it from the 'stochastic equilibrium unemployment rate' (given by (7) above). Clearly, in exploring Okun's law our focus must be on the *relative* movements in entry and exit following a shock to GDP growth.

The last two columns of Table 1 provide descriptive statistics for the first-differences in the logarithms of the entry and exit rates, together with the GDP growth rate. As expected, we see that the GDP growth rate is positively correlated with changes in the (logarithm of the) entry rate and negatively correlated with changes in the (logarithm of the) exit rate.

Since all three variables we are interested in (the change in the logarithm of the entry rate, the change in the logarithm of the exit rate and the GDP growth rate) are I(0) and given also that we want to allow for possible interactions between entry and exit rates[26] with GDP growth treated as exogenous, the appropriate way to approach the data is by using Vector Autoregression (VAR).[27] We again include a slope dummy to allow for asymmetry.[28]

The results of the VAR are set out in the second and third data columns of Table 2. In an attempt to provide an efficient description of the results we will focus our attention on estimated coefficients that have a p-value ≤ 0.10 (estimated coefficients with a p-value greater than 0.10 will be treated as having a 'true' value of zero).

What insights into Okun's law and the labour market in Australia result the equations for the first difference in the logarithms of entry and exit rates? To answer this question we will consider two scenarios. The first scenario involves an increase in the (positive) rate of GDP growth when the economy is not in a recession (obviously consequences of a decrease in the rate of GDP growth when the economy is not in a

26 We saw earlier that inflow and outflow rates are interdependent.

27 The AIC criterion has been used to determine the appropriate lag lengths.

28 Including a shift dummy for recession periods yields coefficients on the dummy which have very high pvalues. As a result, we drop the shift dummy (but retain the slope dummy).

recession simply involves changing the signs in what follows). The second scenario involves a further decline in the rate of GDP growth when the economy is in a recession (obviously consequences of an increase in the rate of GDP growth when the economy in a recession simply involves again changing the signs in what follows). In each scenario we will focus on what it is about the effect of economic growth on the entry and exit rates that results in the unemployment rate changing in the direction consistent with Okun's law.

An increase in the rate of GDP growth when the economy is not in a recession

The entry in the first column of the second row (labelled "GDP growth rate") of Table 2 tells us, not unexpectedly, that the increase in the growth rate leads to a fall in the unemployment rate. What must be happening to unemployment entry and exit to bring this about? The third and fourth columns of the second row give us that information. We see that in response to an increase in the growth rate, the entry rate falls, thus tending to lower the ratio of unemployment to employment and the unemployment rate below what it would otherwise be. We also see that in response to a higher rate of economic growth the exit rate rises and this will also be tending to lower the ratio of unemployment to employment and thus the unemployment rate below what it would otherwise be. Taken together these results are consistent with a rise in the rate of economic growth resulting in a lower rate of job separations and a higher rate of job finding than would otherwise be the case.

A decrease in the rate of GDP growth when the economy is in a recession

The entry in the first column of the third row (labelled "Slope dummy for recession") of Table 2 tells us that the Okun coefficient varies, depending upon the state of the economy and specifically that, if the economy is growing below the trend rate, the effect of a given change in the growth rate upon unemployment rate will be greater (more negative) than if the economy is growing at or above the trend rate. What must be happening to unemployment entry and exit to bring this about? Again, the third and fourth columns of the third row give us that information. Notice that in recessions we estimate that the impact of a change in the growth rate on the change in the entry rate is larger (specifically, more negative) than at other times, while there appears to be no significant impact of a change in the growth rate in recessions on the exit rate. In short, the asymmetry in the response of the unemployment rate to changes in the GDP growth rate is likely due to factors which effect the rate at which job separations occur. How can we explain the presence of asymmetry? Some time ago Axel Leijonhufvud (1973) introduced the idea of a 'corridor' "by which he meant that when shocks are small, an economy functions relatively smoothly "within a corridor", but large shocks can generate instability and change the dynamics completely" (Farmer, 2022).[29] The large shocks which he refers to are failures of effective demand of such a magnitude that agents are constrained in their actions and their hopes (expectations) of a return to 'normalcy' in the short-run are dashed. In relation to employment this results in a situation where firms will not simply reduce hours in the belief that a reduction in sales is firm or industry specific and/or only temporary but will instead reduce the number of employees.

Returning to the empirical results reported in Table 2 we notice that the consequences for unemployment of a shock to GDP are greater in the second case discussed above (a decrease in the rate of GDP growth when the economy is in a recession) than in the first case (an increase in the rate of GDP growth when the economy is not in a recession). If we use the point estimates of coefficients where the p-value is less than 0.10 we see that a downturn involving a 1 per cent fall in the growth rate will result in a rise in the ratio of unemployment to employment of 0.0577 per cent (*en* rises by 0.0156 per cent + 0.0359 per cent while *ex* falls by 0.0062 per cent) per period while an upturn involving a 1 per cent rise in the growth rate will result in a fall in the ratio of unemployment to employment of 0.0218 per cent (*en* falls by 0.0156 per cent while *ex* falls by 0.0062 per cent) per period. Clearly the behavior of the entry and exit rates are such that in the downturn (cet par) the unemployment ratio rises relatively 'fast' while during the recovery (cet par) the unemployment ratio falls relatively slowly. One possible explanation for this could be in terms of the age profile of firms. During the downturn one would expect firms with relatively high labour costs (in the context of a 'vintage model' one would expect these to be the oldest firms in the industry) to shed labour at a higher rate per unit of output than the labour hiring rate per unit of output of the (likely newer and thus lower labour cost) firms which survive and expand in the recovery.

Concluding remarks

Logic dictates that, if the unemployment rate changes in a systematic way in response to variations in the rate of economic growth, then at least one of the unemployment entry and exit rates must change in a systematic way in response to variations in the rate of

29 Leijonhufvud envisages a world in which the economy "is likely to behave differently for large than for moderate displacements from the "full coordination" time-path. Within some range from the path (referred to as "the corridor" for brevity), the system's homeostatic mechanisms work well, and deviation-counteracting tendencies increase in strength. Outside that range these tendencies become weaker as the system becomes increasingly subject to "effective demand failures" (Leijonhufvud, 1973, p 32).

economic growth. We have seen that this is indeed the case and that the unemployment entry and exit rates appear to respond in ways that make sense in the light of economic theory. We have also found that the asymmetry in the relationship between GDP growth and the unemployment rate reflects the impact of changes in GDP growth on the entry rate and not the exit rate.

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