Evaluating Australian Government Policies Using Administrative Microdata

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A thesis submitted for the degree of

Doctor of Philosophy

The Australian National University

Crawford School of Public Policy

In service of the richly diverse and multicultural Australian community

Disclaimer

I hereby declare that the work undertaken in this thesis has been conducted by me, and that I have made significant contribution to each of three Chapters in this thesis. I conducted this work between February 2021 and June 2025, during which period I was a PhD student at the Australian National University. This thesis, in whole or any part of it, has not been submitted to this or any other university for a degree.

The first Chapter is coauthored with Professor Robert Breunig and Jonathan Hambur. My contribution to this Chapter is as follows: I wrote the paper, compiled the literature review, conducted legislative research, designed the econometric identification strategy and conducted the difference-in-difference estimates. The second Chapter is coauthored with Jonathan Hambur and David Hansell. My contribution to this Chapter is as follows: I designed with all three strategies to track mergers and acquisitions using administrative data, conducted legislative research, wrote the paper, compiled the literature review and conducted the econometric analysis. I also implemented two out of the three strategies, including data cleaning and data construction. The final Chapter is coauthored with Professor Robert Breunig and David Hansell and my contribution to t his Chapter is as follows: I came up with the analysis strategy, specified half of the estimated models, wrote the paper and conducted the literature review.

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3 August 2025

Acknowledgements

I would like to thank my husband Owen Freestone for his unflagging support over the years, my sons Alexander and Thomas for their chaos and cuddles, and my friends for their help and sage guidance. I would also like to acknowledge the generous support of the Sir Roland Wilson Foundation PhD Scholarship Program.

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Overview

The rapid expansion of linked administrative microdata has revolutionised the scope of empirical policy research. Researchers now have unprecedented access to individual- and firm-level data, enabling longitudinal analysis across linked datasets and facilitating the study of complex interactions between economic agents. As the data-sharing ecosystem continues to evolve, the potential for answering previously intractable policy questions grows exponentially.

This thesis comprises three standalone Chapters, each addressing a distinct policy issue through the lens of different administrative microdatasets. While the Chapters vary in their data sources, methodologies, and policy implications, they are unified by their reliance on unit record-level data curated by public sector institutions. The breadth of topics—ranging from business tax policy to mergers policy and human resource strategy—illustrates the versatility and value of administrative microdata in informing diverse areas of public policy.

Importantly, the third chapter contributed directly to the development of the Australian Public Service's (APS) first employment strategy for culturally and linguistically diverse staff. Its findings were instrumental in shaping the Senior Executive diversity targets announced by the APS in April 2024, underscoring the practical impact of this research on public policy formulation.

The first Chapter uses Australian tax and survey data to estimate the effect of several business investment tax breaks, including tax credits and instant asset write-offs, implemented over the past 15 years. To do so we exploit discrete eligibility cut-offs for each policy. We find that the policies implemented during the Global Financial Crisis had a material effect on investment. The responses are larger for unincorporated businesses, possibly reflecting the fact that they are not subject to dividend imputation, which provides evidence in favour of the 'old view' of corporate finance. However, we find more limited evidence of an effect for other policies, including those implemented to address COVID-19, though we do find some tentative evidence that declines in small business tax rates stimulated some investment. By analysing all seven business investment support policies that have been implemented since 2009, we present the most comprehensive analysis of these policies ever conducted in Australia.

The second Chapter presents the first mergers and acquisition database using linked administrative microdata in Australia. At a high level, it is well understood that mergers and acquisitions (M&A) can have an important bearing on competition, broader market outcomes and productivity over time. However, the absence of any formal requirement in Australia for merger parties to notify the regulator has contributed to a systematic lack of data, evaluation, and research on the impact of M&A in an Australian setting. This paper takes an important first step in bridging this gap, by novelly combining a number of administrative datasets and methodologies to infer when M&A transactions have occurred in the Australian market over the past 15 years. First, clusters of employees are tracked between firms in a linked employer-employee database. Second, we track companies moving between tax consolidated groups to infer where a merger or acquisition has occurred. Lastly, we look at merger notification forms submitted by firms to the Australian securities regulator. This yields a total of around 1,500 mergers a year. We find that less productive firms are more likely to be targets, while large complex entities are most likely to be acquirers.

The third Chapter presents analysis of promotion and retention outcomes for different cohorts in the Australian Public Service using the central personnel database held by the Australian Public Service Commission. Using data on all Federal public servants and their promotions and separations (leaving) over the period 2000-2020, we find that over the past twenty years staff from a non-English speaking background (NESB) have endured significantly lower career advancement in the Australian Public Service despite being less likely to separate from the service.

Their lower promotion prospects are significantly more marked towards the higher ranks in the service. These lower promotion prospects for NESB staff are only partially explained by language proficiency or cultural assimilation. The unexplained remainder could reflect a penalty for having non-European features. For comparison, over the same period women have become more likely to be promoted to senior ranks than similar men and just as likely at junior ranks. Disability lowers promotion prospects at all ranks but the senior service and Indigenous staff face much lower promotion prospects at lower ranks.

Chapter 1

When are investment tax breaks effective?

1.1 Introduction

Business investment is crucial for economic growth and prosperity. It contributes to productivity, the key driver of living standards, by raising the amount of capital available per worker (capital deepening) and by embodying technological advances. Business investment also plays an important role in economic cycles: while it accounts for only around 11 per cent of GDP in Australia, it has long been recognized as one of the most volatile and significant components of output across the cycle (Kydland and Prescott 1982). Given these long- and short-term considerations, policymakers around the world remain attracted to policies to promote investment both during 'normal' times and in response to adverse economic shocks.[1]

Australian policymakers are no exception. Over the past two decades they have introduced numerous investment tax breaks (ITB) to stimulate investment. These have been used as a structural tool to raise investment in normal times and as a cyclical tool to stimulate investment during downturns such as the global financial crisis (GFC) or the COVID-19 pandemic. While the various policies differed in detail, all increased the (net present) value of depreciation expenses that firms could use to lower their taxable income. Hence, such policies generate a fiscal cost in terms of forgone tax revenue. For example, the tax incentives introduced in 2019 in Australia to support investment for medium-sized businesses were estimated to cost the government $400 million over the four years following implementation (Australian Government 2019). It is therefore important to understand the effects of these policies to determine their cost effectiveness.

In this paper, we examine the effectiveness in stimulating additional investment of seven distinct policies implemented in Australia between 2009 and 2021. Examining a suite of policies under varying macroeconomic conditions in one country allows us to better understand the macroeconomic context in which ITB policies can increase or fail to increase investment and to understand which design features may lead to program success or failure. We focus on identifying additional investment that would not have occurred in the absence of the policy.

High-quality, unique data make this possible. We use survey data from the Australian Bureau of Statistics (ABS) Capital Expenditure (CAPEX) survey and administrative tax return data from the Australian Tax office, both accessed using the ABS Business Longitudinal Analysis Data Environment (BLADE). We use two different approaches to identifying the effects of these policies, both of which leverage the cut-offs for eligibility in firm size as captured by turnover: Difference in Differences (DD) and Regression Discontinuity Design (RDD).

We find strong evidence that the policies implemented during the GFC increased investment. However, our analysis suggests that other policies implemented during the 2010s and in response to the COVID-19 pandemic had little substantive effect on firm investment.

[1] For example, the United States, Netherlands, and South Korea all used investment tax incentives during the 2009 Global Financial Crisis (GFC). More recently, the 2017 US tax reform incorporates a significant investment tax incentive in the form of a 100% deduction in the year of purchase.

Our paper makes several contributions to the literature. First, it adds to our knowledge of business investment incentives. By considering seven distinct programs with different rules and eligibility criteria implemented under different macroeconomic conditions, but in a single country, it allows us to learn about heterogeneity of effects with respect to firm size, generosity, uncertainty and cyclical economic conditions.

Second, we provide evidence on the effect of dividend imputation in dampening the impact of ITBs, giving insight into the debate on the 'old' and 'new' views of corporate finance. We find that unincorporated businesses, not subject to imputation, respond far more strongly to ITBs. This is consistent with the 'old' view where the marginal source of funds is external, rather than internal. Incorporated companies responded to ITBs during the GFC, but less than unincorporated businesses. Incorporated firms may be heterogeneous in their approach to financing. Some may fund investment from retained earnings (the 'new' view) whereas others may be more dependent upon external funding. It may also be that ITBs affect investment through non-traditional channels, like easing financing constraints that may have been particularly binding during the GFC. Where funding is from non-domestic sources, which is the case for many of Australia's largest incorporated firms, dividend imputation may be less relevant and ITB policies may decrease the cost of capital and stimulate investment.

Third, we provide the first comprehensive study of business investment incentives in Australia. For Australian policy-makers, our findings suggest that ITBs can be an effective counter cyclical tool, but their effectiveness is likely to be highly dependent on the nature of the economic downturn. For example, they seem more likely to be effective in a downturn caused by a dislocation in credit markets, than in a pandemic where the economy is partly shut down. Beyond counter-cyclical policy, smaller policies targeted at structurally raising the level of investment during normal economic times generate few apparent benefits. This does not mean that such policies will never be effective. For example, it may be the policies we studied were too small to have an appreciable effect or were implemented in periods of policy uncertainty. But the results do suggest that something would need to be different to expect a substantial investment response. Finally, we provide some initial evidence that corporate tax rate cuts for small businesses appear to have stimulated additional investment.

The rest of this paper is set out as follows. Section 1.2 gives an overview of the policies we investigate. Section 2 .2 gives an overview of the literature on the effect of investment incentive policies. Section 1.4 provides an overview of our data. Section 1.5 outlines our identification strategies and Section 1.6 presents our results. Sensitivity analysis is included in Section 1.7 and Section 2 .5 concludes.

1.2 Overview of investment incentives in Australia

The 'modern' system of turnover-based investment incentives started in 2007, with the unification of small business tax concessions under a common turnover test of $2 million. Amongst other benefits, these changes enabled businesses that satisfied the turnover test to access instant deduction or 'write off' for depreciating assets costing less than $1,000 and allowed the cost of most other assets to be pooled and depreciated at an accelerated rate. Since then, seven important changes have been made to business investment incentives (See Table 1.1). Three of these - the GFC tax credit and two COVID-related policies - were designed as counter-cyclical stimulus in response to adverse economic shocks. The other four policies expanded eligibility for ITBs in terms of asset value and firm size, in order to 'structurally' raise the level of investment to support productivity.[2] In all cases the ITBs applied only to machinery & equipment, while buildings were excluded. We use this exclusion both as a placebo test, and to differentiate ITBs from the effects of corporate tax rate cuts that coincided with some ITB policies.

The first three policies relate to small businesses with a turnover of under $2 million.

The GFC investment tax credit (GFC 2009) offered a deduction for new business investment in addition to normal depreciation deductions. When the policy was first announced in December 2008 it afforded all businesses an extra deduction of 10 per cent (Swan 2008). This was increased to 30 per cent in the March quarter of 2009 (Swan 2009a). In May 2009 the policy was further changed, to allow for a differentiated benefit by firm size (Swan 2009b). Small businesses were able to deduct a bonus 50 per cent for investment made from 13 December 2008 to 31 December 2009

[2]See Appendix A for more details of these policies.

Table 1.1: Investment incentive policies

Policy	Eligibility criteria Investment tax benefit policy	
	TO limit Instant write off	Asset limit Extra deduction
GFC 2009	\$2m ×	Uncapped, expenditure minimum ✓
SBE 2012	\$2 million ✓	\$6,500 ×
SBE 2015	\$2 million ✓	\$20,000 ×
Medium 2016	\$10 million ✓	\$20,000 ×
Medium 2019	\$50 million ✓	\$30,000 ×
COVID 2020	\$500 million ✓	\$150,000 ×
COVID 2021	\$5 billion ✓	Uncapped ×

SBE: small business entities

for investments costing at least \$1,000 (applied retrospectively to investments made before the adjustment to the policy). Other businesses were allowed to deduct a bonus 30 per cent on investments over \$10,000 for investments committed to before 30 June 2009 and a 10 per cent deduction for those committed to during the second half of 2009. We focus on the second half of 2009 for our analysis, where the subsidy rates differed substantially by firm size.

The small business incentive 2012 (SBE 2012) gave businesses with a turnover up to \$2 million an increase in the instant asset write off threshold from \$1,000 to \$6,500 from 1 July 2012. Legislation enacting the increase from \$1,000 to \$5,000 was contingent on the passage of the Mineral Resource Rent Tax legislation[3] and the further increase to \$6,500 was contingent on the passage of legislation related to emissions reductions. This increase in the asset threshold was subsequently unwound from 1 January 2014 and reset to \$1000 until 2015 when the next set of incentives were introduced.

The small business incentive 2015 (SBE 2015) increased the asset threshold from \$1,000 to \$20,000 from 12 May 2015 to 30 June 2018. However, small businesses also received a 1.5 percentage point tax cut from July 1 2015. Firm behavior during this period will be affected by both the instant asset write off and the corporate tax rate cut. We focus on an estimation window up to December 2015 to avoid possible confounding with the Medium 2016 policy discussed below. Table 1.2 shows the evolution of the corporate tax rate that applied to small businesses during our analysis period. This period includes both changes to rates and changes to the definition of small business.

The next two policies extended instant write off benefits to medium-sized businesses.

The expanded business incentive 2016 (Medium 2016) extended the instant asset write off to businesses with a turnover of up to \$10 million for expenditure up to \$20,000 from mid-2016. The same package also gave these businesses a tax rate cut from \$30% to \$27.5% (Table 1.2). Since these reforms were introduced at the same time, the policy period covers both policies.

The medium sized businesses 2019 (Medium 2019) policy followed Medium 2016 and the instant asset write off was extended to businesses with a turnover of less than \$50 million, allowing them to fully expense capital investments made between 2 April 2019 and 30 June 2020 for assets that cost less than \$30,000. However, this policy effectively

[3] https://www.ato.gov.au/businesses-and-organisations/corporate-tax-measures-and-assurance/large-businesses/in-detail/tax-transparency/corporate-tax-transparency-report-for-the-2014-15-income-year/minerals-resource-rent-tax

Table 1.2: Corporate tax cuts

	Small business rate	Small business threshold
2014-15	30%	$2m
2015-16	28.5%	$2m
2016-17	27.5%	$10m
2017-18	27.5%	$25m
2018-19	27.5%	$50m
2019-20	27.5%	$50m
2020-21	26%	$50m
2021-22	25%	$50m

ended on 11 March 2020 as the Australian government introduced a new investment incentive from 12 March 2020, in response to the COVID pandemic.

The large businesses incentive (COVID 2020) was available from 12 March 2020 to 6 October 2020. Under this policy, larger businesses had access to a range of new incentive measures. Firstly, businesses with a turnover of up to $500 million had access instant asset write off for capital assets costing less than $150,000. Coverage included past purchases - that is, for assets purchased after 2 April 2019 and before 31 December 2020. Second, an accelerated depreciation rate of 50 percent was available to businesses in the year the asset was purchased for assets costing more than $150,000 purchased in the 2019-20 and 2020-21 income years.

Full expensing measures for very large businesses (COVID 2021) came hot on the heels of this program and were available from 6 October 2020. This program allowed businesses with a turnover of up to $5 billion to immediately deduct the full cost of investment with no dollar limit.

We can make some general observations in relation to the generosity of these policies. The GFC investment tax credit was the most generous of the policies because asset values were uncapped, and businesses were able to 'double dip' - to access an extra deduction, together with normal depreciation allowances in future years. In contrast, all other tax incentives only allowed a bring-forward of depreciation deductions from future years, basically providing only a timing benefit. The COVID 2020 and 2021 policies were the most generous bring-forward policies with much higher or uncapped asset limits and cover for businesses with much higher turnovers than previous policies. The 2015 and 2016 policies were not only less generous, but were rendered less valuable by corporate tax rate cuts implemented at the same time (since lower tax rates imply that each dollar of deduction is worth less in foregone tax).

One caveat is the difficultly of measuring the impact of these policies on firms' cost of capital. This is because we do not observe the proportion of each firm's assets that fall below the asset cost cap, nor do we observe the tax life of these assets (with longer-lived assets benefiting more from instant write off). For example, firms that primarily use inexpensive assets (costing less than the cost cap) with long tax lives would benefit more than firms that use expensive assets (costing more than the cost cap) or firms that use assets with short tax lives.

1.3 Literature

Jorgenson and Hall (1967) first analyzed the impact of tax incentives on business investment and the intervening (nearly) sixty years have seen many economies implement large-scale business tax reforms with an aim of stimulating investment, both in normal times and as a counter-cyclical tool. Questions around the efficacy and cost effectiveness of such measures remain a live part of the policy debate.

Investment tax incentives are generally thought to affect investment through two channels. The 'traditional' user cost channel, and the 'non-traditional' financing frictions channel.

The user cost channel postulates that firms will invest as long as the marginal benefit of investment is higher than the cost. Increasing tax deductions for investment expenditure reduces the cost (often referred to as the user cost of capital (UC)) by increasing the present value of depreciation allowances that firms can use to lower their tax. The UC, as expressed by Jorgenson and Hall (1967), is:

$$UC = P * M * \frac{1 - \tau Z}{1 - \tau} \tag{1.1}$$

where P is the real price of investment goods, M is the weighted average cost of funds (debt and equity), and τ is the business tax rate. Z is the ratio of the present value of future depreciation allowances, relative to the initial purchase price of the asset. These allowances permit businesses to deduct the cost of their capital investment from their taxable income over several years, with the period approximately reflecting the economic life of the asset. By increasing or bringing forward the timing of these allowances, investment incentives can increase Z and so lower the UC.

A permanent policy change that lowers the UC leads to a burst of investment as firms adjust to their new higher desired capital stock.[4] Investment may remain higher going forward as well, as firms invest to maintain the higher capital stock. Temporary policies may have a larger and more immediate effect as firms bring forward investment to the current period when it is cheaper (Abel 1982). However, empirically this bring-forward effect may be hard to detect, particularly in the case of long-lived assets as the future 'hole' in investment could be spread over many years (House and Shapiro 2008).

Imputation systems such as Australia's change these costs and benefits. In Australia, company tax operates as a withholding tax. When dividends are issued to individuals, those individuals receive a credit for the company tax paid. Individuals are taxed annually on all of their income and can claim the credits for tax already paid at the company level. This reduces the tax liability for dividends for those on a personal income tax rate higher than the corporate rate and results in a refund of corporate tax paid for those individuals whose personal, marginal rate is less than the corporate rate. In particular, as they provide the end owner of the company with a tax offset for the tax paid by the company, they can 'wash out' the benefits of the depreciation allowances. Dividend imputation has been removed in many countries, including the U.K. and New Zealand, in line with lowering corporate tax rates. They remain an important feature of the Australian system.

Under the 'old view' of corporate finance, where businesses fund new investment through raising equity, the UC can be augmented for imputation as (Officer 1994):

$$UC = P * M * \frac{1 - \tau(1 - \gamma)Z}{1 - \tau(1 - \gamma)} \tag{1.2}$$

Imputation is captured by the term $\gamma \epsilon [0, 1]$, which measures the value of a dollar of tax paid at the company level to shareholders. This value reflects the fact that, under dividend imputation, tax paid at the company level is a credit for personal income tax for resident shareholders. If all shareholders are domestic, as may be the case for small firms, and in the presence of full refundability of imputation credits, the value of γ is one – tax paid at the company level lowers shareholders' taxes dollar-for-dollar. In this case increases in Z do not affect the cost of capital nor investment. If some shareholders are non-residents, as may be the case for larger firms, γ may be below 1.

In contrast, the 'new view' posits that the marginal source of funds for firms is retained earnings. In this case the imputation system has little influence on the UC.

These two views of corporate finance lead to two very different conclusions regarding whether firms that are subject to imputation will respond differently to an ITB than those which are not. Under the old view, firms not subject to imputation (i.e. unincorporated businesses) should respond more strongly. Under the new view, both firm types should respond similarly.[5] As such, firm responses to ITBs can be used to assess which view of corporate finance is most consistent with the empirical evidence.

Numerous studies have examined similar ITBs outside of Australia. Empirical studies in the US (House and Shapiro 2008; Zwick and Mahon 2017) and UK (Maffini, Xing and Devereux 2019) found strong investment responses to tax incentives (and associated decreases in the user cost of capital).

[4] Given tax incentives work through this UC channel, these policies have often been used to assess the effect of changes in the UC on investment more generally. They are seen as providing more plausibly exogenous variation than changes in financing costs (Cummins, Hassett and Hubbard 1994) and are less prone to measurement error.

[5] For a more detailed discussion see Sobeck, Breunig and Evans (2022).

House and Shapiro (2008) test if businesses increased their expenditure on longer lived assets, and for any change in aggregate investment behavior in response to a change in policy. To examine asset lives, they use data from the Bureau of Economic Analysis to construct a quarterly panel of investment quantities and prices by asset type. They match 36 asset types to the IRS depreciation schedule to track eligible and ineligible investment as well as short/long asset lives between 1959 and 2005. A structural model is then estimated to provide a baseline for investment activity, GDP and employment without the bonus investment. House and Shapiro (2008) then compare forecast errors across asset types. A strong response to the tax break was found in terms of the investment composition, with an investment supply elasticity of between 10 and 20 per cent. However, only modest increases in aggregate output and employment were found, as the policy narrowly benefited a small subset of investment goods.

Zwick and Mahon (2017) study the same bonus depreciation policy as House and Shapiro (2008) but use detailed IRS corporate tax return data that include information on investment in equipment and structures. In 2008, the sample represented about 1.8 per cent of the total population of 6.4 million C and S corporation returns. In each non-bonus year, the authors compute the share of eligible investment a firm reports in each asset-life and property category. They then compute the present discounted value of one dollar of deductions for eligible investment, and combine this with the eligible investment shares to construct an industry-average asset life. As the policy raises net present value of longer-lived investment by more, they use this variation in asset lives in a difference in difference regression to identify the policy effect. They find evidence that the policy affected investment. They also find evidence that the policy had a larger effect on the investment of firms that appeared to be financially constrained, indicating that the policy worked at least partly by loosening constraints.

Maffini et al. (2019) study UK corporate tax returns to analyze the impact of a 2004 change in policy that allowed more firms to access small business depreciation concessions, which in turn allowed for a 40 per cent depreciation rate compared to the 25 per cent available for larger companies. Similar to what we do, they exploit this exogenous change in the qualifying thresholds and compare the response for companies newly qualified for the greater depreciation deductions to those that remain ineligible. Consistent with the US studies, Maffini et al. (2019) find a substantial positive effect of more generous depreciation allowances on firms' investment. Relative to the control group, the depreciation allowances raised the investment rate in eligible assets of newly-qualified companies by between 2.1 and 2.5 percentage points within three years of the change.

Zhang and He (2018) and Liu and Mao (2019) analyze the effect of a permanent 17 per cent tax credit for fixed investment for six industries in Northwest China between 2004 and 2009. Using geographical restrictions to identify the policy effect, Liu and Mao (2019) found that the tax credit raised fixed investment of eligible firms by 28 per cent on average during 2004–2007, relative to 2001–2003, corresponding to a user cost elasticity of 1.84. The strong response by firms found by Liu and Mao (2019) is consistent with Zhang and He (2018), who found that, on average, the reform raised investment of the treated firms relative to the control firms by 38.4 per cent.

Australian evidence is sparse, partly due to historic data availability issues. Rodgers and Hambur (2018) analyze the effect of tax breaks for machinery and equipment during the GFC (the first of the seven reforms we consider in this paper). They use RDD and DD methods around the turnover threshold to compare the investment of small and large businesses using business tax microdata and unpublished survey data from the Australian Bureau of Statistics.

Consistent with the difference in corporate taxation regimes (i.e., classical taxation in the US and dividend imputation in Australia) and the 'old view' of corporate finance, Rodgers and Hambur (2018) find a lower responsiveness of investment to the ITBs compared to Zwick and Mahon (2017), as measured by the elasticity of investment. However, they find a much larger elasticity, more in line with the US studies, when focusing on unincorporated businesses who face a classical taxation regime similar to US corporations. They find some evidence that incorporated companies also responded. Given the policy was targeted at smaller companies who have very few non-resident shareholders, they argue that under Australia's dividend imputation system, γ equals one for these companies. They conclude that their findings suggest the policies worked partly by relaxing financing constraints.[6] Our results presented

[6]The broader literature on the value of γ is mixed. Many large Australian companies raise equity from international investors, who derive no benefit from dividend imputation. As such, γ is unlikely to be 1 for these businesses. Applied evidence based on samples of listed companies finds a range of values for γ, see Swan (2019); Sobeck et al. (2022). At the same time, studies overseas have found evidence in support of the 'new view' (i.e. γ is 0), with Yagan (2015) finding evidence that cuts to dividend taxes in the US in 2003 had little effect on investment.

below are consistent with this previous research on Australia, which only examined one of the seven policies that we examine.

1.4 Data

We merge survey data from the Australian Bureau of Statistics (ABS) with business taxation administrative data from the Australian Taxation Office (ATO) to construct our sample. This provides us with two different sources of investment data. The first is the Private New Capital Expenditure and Expected Expenditure (CAPEX) survey, covering around 10,000 firms each quarter. Consistently large investors as determined by the ABS (large mining companies, banks and a few other large firms) are surveyed every quarter, while the remainder are sampled with stratification by industry, location and employment size, with firm details drawn from the administrative business register. CAPEX data have the advantage that they provide investment by asset type: machinery and equipment (assets mostly eligible for the investment incentives we consider) and buildings, structures and mining (assets ineligible for the investment incentives we consider). However, the sample is too small for our RDD. Once combined with other taxation data (see below) we have a panel with around 90,000 businesses and around 667,000 observations spanning the period 2000-01 to 2018-19. See Appendix B for summary statistics of the data we use to analyze each policy.

Our second source of investment data is capital expenditure reported in firms' Business Activity Statements (BAS). These are available quarterly covering the period 2001-2021. As these data are reported by almost all firms, the sample is very large[7]. However, eligible and ineligible investment are not separately reported in these data.

We consider both the intensive and extensive margins. The intensive margin is the (natural) log of investment. For the extensive margin, our dependent variable is the log odds ratio for the share of firms investing, calculated at the industry division-turnover category level, as in Zwick and Mahon (2017).[8] The extensive margin is particularly relevant for the analysis of small business policies, as only around 25 per cent of small firms (<20 staff) invest each quarter based on tax data, compared to around 80 per cent of large firms (200+ staff). In our RDD design we focus only on the intensive margin.

These investment data are combined with other annual tax data covering a rich set of information on business type, turnover, assets, liabilities and ownership structure. The tax data also include details of which businesses connect to others through a business group identifier. This aggregation is useful since the legislated turnover tests are on an 'aggregated turnover' basis, which includes the annual turnover of not just the primary business but also any other controlled or affiliated businesses in related business groups. Lastly, the tax data allow us to differentiate between different legal structures: companies, partnerships, trusts and individual entities. These distinctions are important in the Australian context given companies are subject to a dividend imputation regime, which may limit the value of ITBs to the firm.

We exclude the mining sector to eliminate any potential effects from the mining boom. We also exclude the public sector (based on ABS Standard Economic Sector Classifications of Australia). We exclude the finance sector from the RDD estimates, due to conceptual difficulties in using tax data to measure investment for this sector.

1.5 Identification Strategies

To identify any effect of the ITBs we use both a difference-in-differences approach and a regression discontinuity approach. As explained below, each identify different impacts and rather than focus on one, we use both to see if there is any effect of the ITB policies. Our assessment of the impact of the policies will be based on an examination of the combined evidence across these approaches.

[7] From 2017/18 small firms below $10 million in turnover no longer needed to report on their capital expenditure in the BAS. However, all policies from this point on were aimed at larger firms, so this does not affect our analysis.

[8] More formally, it is defined as $\ln \frac{P_{n,s,t}(Investment_{i,t}>0)}{1-P_{n,s,t}(Investment_{i,t}>0)}$, where n indicates industry, s size and t time

Difference in differences

Our first approach is a DD model. We exploit the timing of the policies and the exogenous qualifying turnover thresholds to identify the impact of the policy by comparing qualifying and other firms during and outside of the policy period. The treatment and control groups are summarized in Table 1.3. The financial year in Australia runs from July to June.

Table 1.3: Summary of DD Identification Strategies

Policy	Treated	Control	Quarters
GFC policy 2009	TO < \$2m	\$2m < TO < \$5m	Sep 2009 - Dec 2009
SBE 2012	TO < \$2m	\$2m < TO < \$5m	Sep 2012 - Dec 2013
SBE 2015	TO < \$2m	\$2m < TO < \$5m	Sep 2015 - Dec 2015
Corporate tax cut	TO < \$2m		Jun 2015
Medium 2016	\$2m < TO < \$10m	\$10m < TO < \$20m	Sep 2016 - Jun 2017
Corporate tax cut	TO < \$10m		Sep 2016
Medium 2019	\$10m < TO < \$50m	\$50m < TO < \$60m	Jun 2019 - Mar 2020
Corporate tax cut	TO < \$50m		Sep 2018
COVID 2020	\$50m < TO < \$500m	\$500m < TO < \$600m	Mar 2020 - Jun 2020
COVID 2021	\$500m < TO < \$5b	\$5b < TO < \$6b	Sep 2020 - Jun 2021

Quarters refer to the end month of the quarters during which we evaluate a policy impact.

Our regression takes the following form.

$$Inv_{ijt} = \alpha + \beta_1 d_t^P + \beta_2 d_i^T + \beta_3 (d_t^P \times d_i^T) + \theta_i + \gamma X_{ijt} + D_t + IND_j \times D_t + \epsilon_{ijt} \tag{1.3}$$

where $Inv_{i,t}$ is our measure of investment (intensive or extensive margin) for machinery and equipment for business i in industry j in period t, d_t^P is a dummy that equals one in the periods of operation of the relevant policy, and dummy d_i^T is equal to one for businesses that meet the relevant turnover test. We also include a number of controls in the model to help with identification and with precision. First, we include firm fixed effects θ_i to capture time-invariant firm-specific factors influencing investment. We also include additional time-varying, firm-level controls to capture other factors that could be influencing investment, captured in $X_{i,t}$. Specifically these are full-time equivalent employment and deciles of the distribution of firm turnover. We also include a vector of quarterly dummies, D_t, to account for seasonal patterns in investment. And we include industry*time fixed effects ($IND_j \times D_t$) to capture heterogeneous industry level trends and conditions, which might be particularly important during the GFC and COVID as different industries were differentially exposed to these shocks. Our identification strategy compares small and large businesses within the same industry.[9] Standard errors are clustered at the firm level for intensive margins and industry levels for extensive margins.[10]

To define a firm's eligibility, we turn to the tax code. The code states that a firm is small if their revenue in a period is below a certain threshold. Several different periods can be used for this assessment under the tax code eligibility rules:

1. Revenue in year *t*;
2. Revenue in year *t-1*; or
3. Revenue in year *t-2* if the firm had a reasonable expectation when it undertook the investment that revenue in year *t* would be below the threshold.

[9] Industry is measured at the division level and takes 19 possible values. The inclusion of these industry dummies will also control for differing asset lives across industries, which determine how beneficial the various policies will be for different industries.

[10] We focus on the average effect of policies in the treatment period (which covers two through five quarters, depending upon the policy). If we instead estimate individual effects for each quarter, our conclusions are similar.

This final category, which combines revenue in year *t-2* with expectations about revenue in year *t*, was designed for firms that may have had a windfall gain in year *t-1* and for whom revenue in year *t-2* is more "representative" of their normal revenue. Given firms may not know time *t* sales during the year when investment decisions are made, they are allowed to rely on a reasonable expectation. We don't use firms that rely on this rule for the DD regressions, but they are used for the RDD identification in combination with information about actual turnover in time *t* and $t-1$ as discussed below.

For the purposes of the DD regressions, we use revenue in year *t-1* in assessing whether the firm qualifies for the policy, as in Rodgers and Hambur (2018). As discussed below, for our RDD regressions we take a different approach, exploiting the third category noted above to get very tight identification.

As noted above, one concern with identifying the effects of these ITBs is that some coincided with changes in the corporate tax rate for firms based on the same threshold. Table 1.2 shows the changes in the tax rate over time. Of particular concern, the changes in 2015/16 and 2016/17 coincide perfectly with the 2015 and 2016 ITBs. The reduction in the corporate tax rate would have simultaneously lowered the value of ITBs for companies, and potentially stimulated additional investment. As such, this may affect our estimated effects for these policies. To assess the degree to which this might be affecting our results, we provide separate estimates for assets which were or were not eligible for the ITB (see Section 1.7 below).

Regression discontinuity design

Another way to exploit the exogenous eligibility threshold is an RDD approach. Similar to DD, this involves looking at differences in outcomes for eligible and ineligible firms. But instead of comparing outcomes more broadly between these groups, it focuses on an area (η) around the policy threshold cut-off, comparing outcomes for firms just above and just below the threshold to determine any discontinuity at the threshold.

The advantage of this approach is that the identification is sharper and requires relatively weaker assumptions– namely that in the absence of treatment there would be no discontinuity at the threshold.[11] However, the approach requires more data and the identified effect, while sharp, is very local and can be hard to extrapolate to an aggregate effect. Given the data requirements, we use the BAS data described above for the RDD estimates.

For identifying the relevant cut-off we adopt the approach of Rodgers and Hambur (2018). This approach focuses on firms that would qualify based on whether their turnover was above or below the threshold in year *t-2*. This helps to minimise any possibility that firms could manipulate their way into treatment.

To isolate these firms, we remove firms that could qualify for the incentives based on their incomes in tax year *t* or *t-1* (i.e. businesses with turnover under the turnover limit in those years). Amongst the remaining firms, the only firms that could use their income in *t-2* to meet eligibility are those that had a reasonable expectation that their income in *t* would be below threshold. The tax rules note that the best way to assess this is revenue in *t-1* (Australian Taxation Office 2017). That is, only firms with revenue a little bit above the threshold in *t-1*, could say they reasonably expect to be below the threshold in *t*.

To meet this final requirement, we remove firms with income in *t-1* above a certain threshold. We use a ceiling of 1.25 times the threshold. The selection rules we use to choose our estimation sample are summarized in Table 1.4.

In summary, we focus on the subset of firms with turnover above the threshold in year *t*, and between the threshold and 1.25 times the threshold in year *t-1*. This group would qualify for the ITB only if their turnover was below the threshold in *t-2*. So we have a clean eligibility cut-off at the threshold to separate qualifying and non-qualifying firms based upon their revenue at time *t-2*.

The RDD can be thought of as estimating a local polynomial for the conditional mean, estimated precisely on either side of the threshold. We estimate this function using local linear, non-parametric regression with a triangular kernel. We implement the automatic bandwidth selection procedure proposed by Calonico et al. (2014) with a triangular kernel. We also also use their bias adjusted p-values.[12] The results are robust to selecting different bandwidths.[13]

[11] For discussions of the theory and practice of the RDD approach, and how it approximates random assignment, see Imbens and Lemieux (2008) and Lee and Lemieux (2010).

[12] We implement this using the `rdrobust` package in STATA.

[13] These results are available from the authors on request.

Table 1.4: Summary of RD Identification Strategies

	TO in *t-2*	TO in *t-1*	TO in *t*
GFC, 2012 & 2015 Policies			
Dropped		TO < \$2m	TO < \$2m
Policy	\$2m-η < TO < \$2m	\$2m < TO < \$2.5m	
Control	\$2m < TO < \$2m+η	\$2m < TO < \$2.5m	
2016 Policy			
Dropped		TO < \$10m	TO < \$10m
Policy	\$10m-η < TO < \$10m	\$10m < TO < \$12.5m	
Control	\$10m < TO < \$10m+η	\$10m < TO < \$12.5m	

For all RDD regressions we cluster standard errors at the firm level.

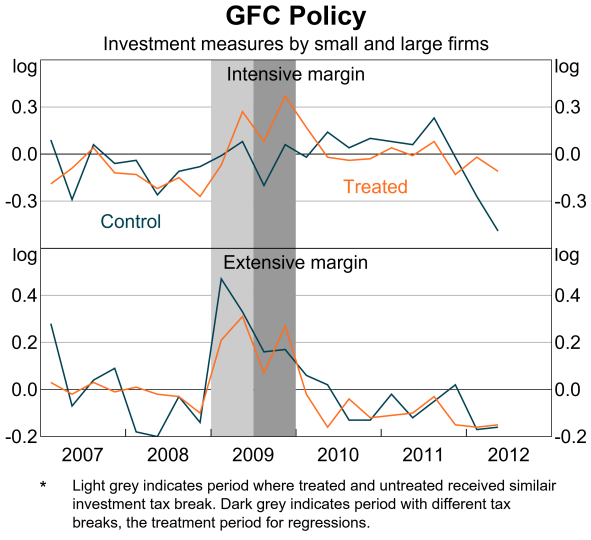
1.6 Results

Below we summarize our empirical results. We split the results into groups of policies: macro-stabilisation policies; structural small business policies; and structural medium business policies.

Macrostabilisation policies

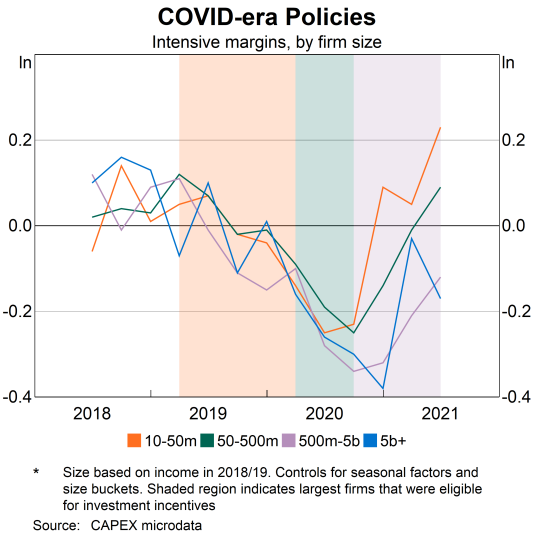
First, focusing on the graphical evidence for the DD approach (see Figure 1.1) we see clear evidence of an effect for the GFC policies: investment for both groups followed a similar pattern, before diverging in the second half of 2009 when the differential tax incentive was in place (dark grey). This was particularly evident at the intensive margin.

Figure 1.1: GFC policy intensive and extensive margins



In contrast, focusing on the COVID-era policies (see Figure 1.2), we see that over this period all firm size groupings follow a broadly similar investment path. Given the overlapping nature of these policies we can visualise them more succinctly compared to the other DD results. We show investment for each group, where the shaded colour corresponds to the largest firm newly eligible for a tax concession. If the policies were affecting investment, we would expect to see each line pick up, relative to the line for the next size group, when we enter the relevant shaded period. For example, we should see the green line pick up in the green shaded section compared to the next size up represented by the purple line. However, there is no evidence for an increase in investment as each group becomes eligible for the incentive, suggesting little evidence of an effect from the policy. All lines follow fairly similar paths.

Figure 1.2: Post-GFC policies



These findings are borne out in the regression analysis (Table 1.5). The GFC tax incentive seems to have successfully raised investment on the intensive margin, with treated firms increasing spending substantially on eligible investment. The effects are larger for unincorporated businesses, consistent with previous findings and the fact that the imputation system should wash out much (if not all) of the benefit for domestically owned companies. This would also be supportive of the 'old view' of corporate finance. Nevertheless, the fact that there is some response among companies suggests that either the ITB is working through other channels, like easing cashflow constraints, or that there is heterogeneity in the source of funding for incorporated firms. Overseas investors do not benefit from imputation and the ITB would lower the cost of capital for firms with overseas ownership or investment.

We see a statistically significant effect on the extensive margin for unincorporated firms suggesting that the policy increased the number of unincorporated firms who made investments. We see a positive effect for incorporated firms as well but the t-value of 1.3 falls below standard significance levels. For all of the DD results we show robust standard errors clustered at the firm (intensive margin) or industry (extensive margin) level; for the RDD results we show robust p-values.

Table 1.5: Difference-in-difference results: Stimulus measures

	Intensive margin			Extensive margin		
	All entities	Companies	Unincorps	All entities	Companies	Unincorps
GFC Policy 2009	0.456***	0.414**	0.870***	0.207*	0.176	0.274**
SE	(0.136)	(0.168)	(0.238)	(0.113)	(0.132)	(0.139)
Observations	7226	4660	2520	46069	24758	21293
COVID 2020	-0.291*			0.138		
SE	(0.150)			(0.219)		
Observations	17701			25643		
COVID 2021	0.404			0.546		
SE	(0.267)			(0.449)		
Observations	5040			6147		

Regressions include controls, except for COVID 2021 intensive margin results which are estimated without controls due to small sample sizes.
Mining is excluded.
Cluster robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

In contrast, we do not find statistically significant results for the COVID policies.[14] There is even some evidence

[14]Due to small sample sizes at higher turnover ranges, we do not include results by firm type for the COVID policies.

suggesting a negative effect at the intensive margin for the 2020 policy, though the confidence interval is wide.

Turning to the RDD approach, graphically we see a clear shift down in investment above the GFC policy threshold (Figure 1.3). This is evident whether we focus on average investment within small sales buckets (blue dots), or a line of best fit using a linear (green dots) or local polynomial model (orange line). This is also evident in the regressions, with a large fall in investment above the threshold, suggesting the ITB raised investment for eligible firms (Table 1.6).[15]

Figure 1.3: Log Residual Investment and Revenue SEP 2009

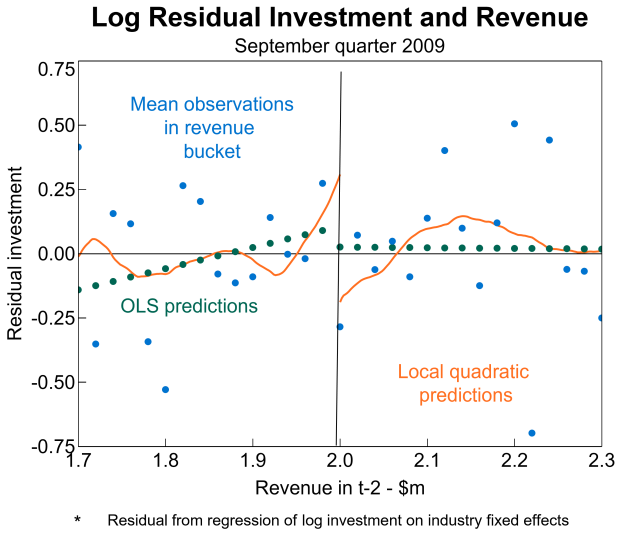


Table 1.6: RDD results: log residual investment for GFC policies

	Mar 2009	Jun 2009	**Sep 2009**	**Dec 2009**	Mar 2010
All firms					
Beta	-0.114	0.006	-0.404**	-0.0358	-0.022
Robust p-value	(0.49)	(0.79)	(0.02)	(0.82)	(0.88)
Bandwidth	328,163	326,907	246,555	467,689	508,608
Effective observations	2,106	2,421	1,692	2,875	2,713
Unincorporated					
Beta	0.005	-0.292	-0.570**	-0.032	0.187
Robust p-value	(0.96)	(0.31)	(0.03)	(0.96)	(0.45)
Bandwidth	315,877	366,361	275,067	385,634	466,038
Effective observations	867	1,084	813	1,089	1,081
Companies					
Beta	-0.127	0.177	-0.154	-0.036	-0.155
Robust p-value	(0.51)	(0.30)	(0.35)	(0.78)	(0.41)
Bandwidth	374,530	353,778	313,475	368,003	560,025
Effective observations	1,332	1,490	1,173	1,457	1,685

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Interestingly, based on the RDD, most of the effect occurred in the first quarter of the policy (i.e. September quarter 2009), with very little evidence of an effect in the second. In some sense this is surprising, since the policy imposes a long period between the outlay and receipt of the tax benefit. The latter only happened after the company lodged its

[15] In the main text, we present graphs of the RDD results for the impact in the first quarter of the policy. In Appendix C, Figures 1.11 through 1.13, we show RDD estimates of the policy impact in the second quarter for which the policy was in place. Some evidence suggests a small effect for the SBE 2015 policy (Figure 1.13) but this policy is confounded by the small business tax cuts we discuss elsewhere in the paper.

return at the end of the tax year (post June 2010). The finding could reflect an announcement effect. However, it could also reflect uncertainty around further changes to the policy, given the policy was changed several times over the preceding year in various government announcements.

The lack of an offsetting effect in the quarters following the end of the policy suggests either the policy led to an increase in investment, rather than just a bring-forward of future investment, or that the bring forward effect was quite drawn out and not readily observable. These results are consistent with Rodgers and Hambur (2018).

While our findings are qualitatively similar to Rodgers and Hambur (2018), the magnitudes differ. This reflects two factors. For the DD we use an indicator variable to identify the 2009 GFC tax credit in contrast to their measure of the intensity of treatment. This modeling choice is for consistency within our paper across the different policies we consider. For RDD we are using quarterly investment data from the BAS, rather than annual income tax data. This allows us to narrow our focus to the affected quarters.

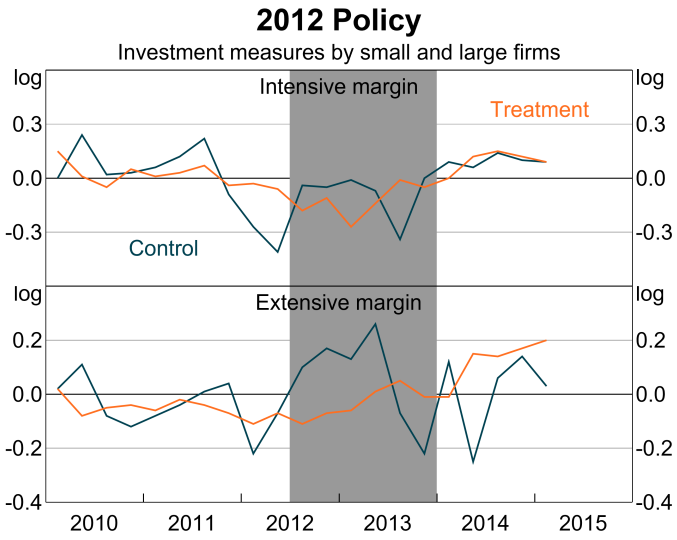
Unfortunately, we cannot assess the COVID polices using RDD because the sample of firms close to the thresholds for the COVID-19 policies is too small. This is due to the very large turnover thresholds–the density of firms becomes very small.

The difference in results across the GFC and COVID policies may reflect the different nature of the economic shocks. The GFC was a financial shock that may have impacted credit supply but did not severely slow real activity in Australia (unemployment did not rise above 6%). This could have meant that generous measures which increased access to funds through the tax system were more likely to be successful. In contrast, the COVID shock resulted in lockdowns across Australia and disruptions in machinery and equipment production globally. These two factors together may have hampered the ability and incentives for business to source and install new capital purchases to take advantage of the investment tax breaks.

Structural small business policies

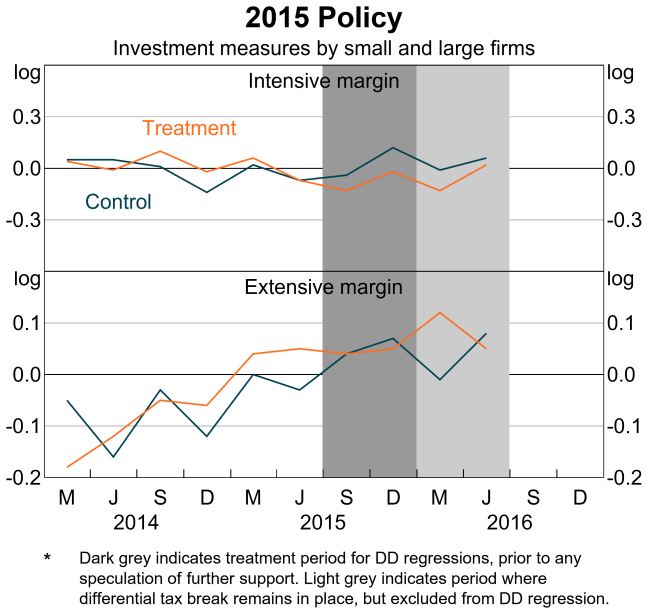
We can also compare the 2009 policy results with other small business policies to interrogate the differences in effects across the policies. For both the 2012 and 2015 policies, very little graphical evidence suggests a policy effect in the DD set-up: investment for the treated and control groups follow similar paths pre-treatment, with no change post treatment (see Figures 1.4 and 1.5).

Figure 1.4: 2012 policy intensive and extensive margins



Consistent with this, the DD regression analysis suggests the 2012 policy did not significantly raise investment (Table 1.7). The 2015 policy appears to have had an effect on investment on the intensive margin for unincorporated businesses. However, the impact is weaker than that of the GFC policy. Furthermore, the 2015 policy may be confounded by corporate tax rate cuts for small businesses implemented at the same time. As discussed in

Figure 1.5: 2015 policy intensive and extensive margins



* Dark grey indicates treatment period for DD regressions, prior to any speculation of further support. Light grey indicates period where differential tax break remains in place, but excluded from DD regression.

section 1.7, we find some evidence that these tax cuts increased investment for incorporated companies. This could have led to some spillovers to unincorporated businesses, so the evidence of any effect of the 2015 policy should be treated with caution.[16,17] The estimates for an impact on the extensive margin are positive but not statistically significant at conventional levels.

Table 1.7: Difference-in-difference results: Small business measures

	Intensive margin			Extensive margin		
	All entities	Companies	Unincorps	All entities	Companies	Unincorps
GFC Policy 2009	0.456***	0.414**	0.870***	0.207*	0.176	0.274**
SE	(0.136)	(0.168)	(0.238)	(0.113)	(0.132)	(0.139)
Observations	7226	4660	2520	46069	24758	21293
SBE 2012	0.0911	0.0308	0.321	0.0431	0.0757	-0.0311
SE	(0.125)	(0.165)	(0.200)	(0.087)	(0.095)	(0.110)
Observations	7253	4704	2521	49474	25920	23534
SBE 2015	0.14	0.070	0.440*	0.138	0.137	0.154
SE	(0.129)	(0.159)	(0.230)	(0.100)	(0.120)	(0.105)
Observations	3911	2631	1270	24172	13298	10857

Regressions include controls. Mining is excluded.
Cluster robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

The RDD results are similar to the DD results. No evidence suggests the 2012 policy affected investment, even when focusing only on unincorporated businesses (Figure 1.6 and Table 1.8). The one significant coefficient (a negative effect of the policy for companies in the June 2013 quarter) may simply be noise. When estimating so many regressions there will be some apparently significant results even when the true impact is zero.

The 2015 policy is associated with some increase in investment, though only for unincorporated businesses (Figure 1.7 and Table 1.9) and with some time lag. The apparent negative impact of the policy in the June 2015 quarter, before the

[16]Some unincorporated businesses, such as trusts, are pass-through companies for corporate entities, thus there may be an affect on investment for unincorporated businesses. We attempt to account for this using ABS information on business links. However, we cannot rule out the possibility that the corporate tax cuts could also affect investment of unincorporated businesses.

[17]We end our DD regression in December 2015 because the tax cuts announced in May 2016 for firms with turnover up to $10 million may have affected the behavior of our control group. Results are broadly similar if we include the March and June quarters of 2016 in the regression.

Figure 1.6: Log Residual Investment and Revenue SEP 2012

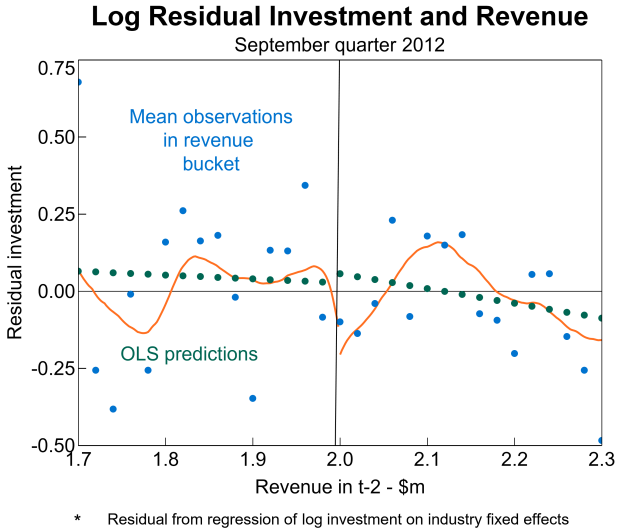


Table 1.8: RDD results: log residual investment for 2012 SBE policy

	Mar 2012	Jun 2012	**Sep 2012**	**Dec 2012**	**Mar 2013**	**Jun 2013**	**Sep 2013**	**Dec 2013**
All firms								
Beta	-0.149	-0.0386	-0.0474	0.162	0.186	0.171	-0.0419	-0.112
Robust p-value	(0.53)	(0.78)	(0.85)	(0.25)	(0.26)	(0.14)	(0.93)	(0.61)
Bandwidth	372,005	421,748	379,932	345,167	380,623	406,370	316,471	411,141
Effective observations	2,765	3,177	2,713	2,556	2,639	2,952	2,402	2,990
Unincorporated								
Beta	0.298	-0.163	-0.149	0.040	0.203	-0.118	-0.121	0.011
Robust p-value	(0.69)	(0.60)	(0.70)	(0.66)	(0.24)	(0.72)	(0.92)	(0.81)
Bandwidth	381,694	482,329	360,767	327,458	434,046	400,103	290,010	367,851
Effective observations	1,298	1,557	1,255	1,170	1,383	1,371	1,059	1,344
Companies								
Beta	-0.288	0.091	0.040	0.187	0.151	0.527**	0.148	-0.173
Robust p-value	(0.21)	(0.77)	(0.91)	(0.32)	(0.70)	(0.02)	(0.41)	(0.43)
Bandwidth	436,224	390,962	401,357	456,602	362,765	323,714	410,413	539,201
Effective observations	1,664	1,614	1,470	1,631	1,312	1,317	1,531	1,813

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

policy began, may be a sign that firms held off investment in anticipation of the policy. If this were the case, however, we would expect to see a strong impact of the policy in the first two quarters where it was in place (September and December 2015). However, there is no measurable impact of the policy in the first 6 months. Any impact appears to occur in March and June 2016 quarters, the period six to twelve months after the policy was introduced. Again, the possibility of confounding effects of corporate tax rate cuts and the announcement of the subsequent medium 2016 policy should be kept in mind.

These lack of responses, particularly for the 2012 policy, may seem surprising in the context of the GFC results, given their identical target groups. However, the 2012 changes happened in a context of heightened political uncertainty, with legislation enacting the increase in the asset cost cap from $1,000 to $5,000 contingent on the passage of the Mineral Resource Rent Tax legislation and the further increase in the cap to $6,500 contingent on the passage of legislation related to emissions reductions. Uncertainty around these other policies, and that the Opposition committed to unwinding these policies if it won government before the expiration of the tax break, may have led businesses to hold off on investment.

Figure 1.7: Log Residual Investment and Revenue MAR 2016

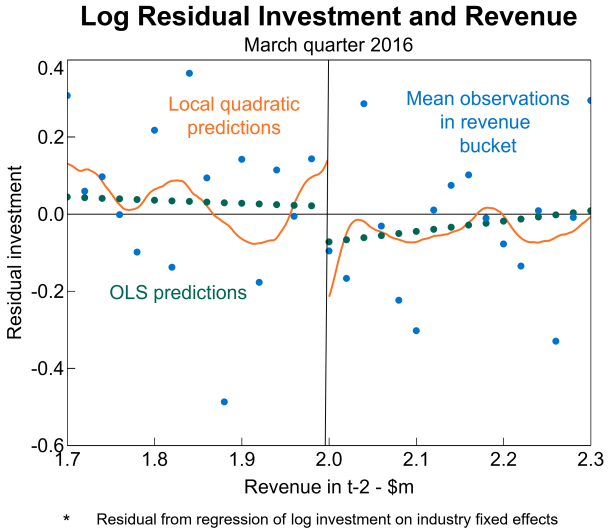


Table 1.9: RDD results: 2015 SBE policy

	Mar 2015	Jun 2015	**Sep 2015**	**Dec 2015**	**Mar 2016**	**Jun 2016**
All firms						
Beta	-0.126	0.226*	-0.012	0.055	-0.306*	-0.279*
Robust p-value	(0.47)	(0.08)	(0.90)	(0.61)	(0.07)	(0.07)
Bandwidth	402,386	344,157	376,464	407,926	326,053	368,267
Effective observations	3,234	3,161	3,129	3,412	2,915	3,333
Unincorporated						
Beta	0.011	0.484**	-0.235	-0.356	-0.518**	-0.567**
Robust p-value	(0.76)	(0.01)	(0.40)	(0.10)	(0.03)	(0.01)
Bandwidth	381,886	386,019	375,716	352,855	315,226	329,403
Effective observations	1,482	1,591	1,408	1,436	1,277	1,399
Companies						
Beta	-0.258	-0.021	0.180	0.446**	-0.136	-0.0512
Robust p-value	(0.20)	(0.92)	(0.52)	(0.03)	(0.47)	(0.76)
Bandwidth	334,682	400,725	385,850	350,061	451,190	484,585
Effective observations	1,492	1,875	1,728	1,688	1,955	2,154

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Some evidence suggests the 2015 policy had a small effect for unincorporated businesses. However, the evidence is weaker and macroeconomically less significant, given that we find smaller aggregate effects than for the GFC policy. This could reflect a number of factors: heightened political uncertainty with the Australian Senate blocking government legislation and culminating in the first double dissolution election since 1987; the smaller nature of the policy; the introduction of the policy at the same time as corporate tax cuts that lowered the value of the investment tax break; and looser financial conditions, which may have meant less scope for the policy to influence companies.

Structural medium business policies

Focusing on the 2016 and 2019 medium firm policies, which cover firms at the $10 million and $50 million thresholds, respectively, again little graphical evidence suggests an effect in the DD approach (See Figures 1.8 and 1.9). The

pre-trends for the extensive margins are quite volatile, suggesting these results should be interpreted with caution.[18]

Figure 1.8: 2016 policy intensive and extensive margins

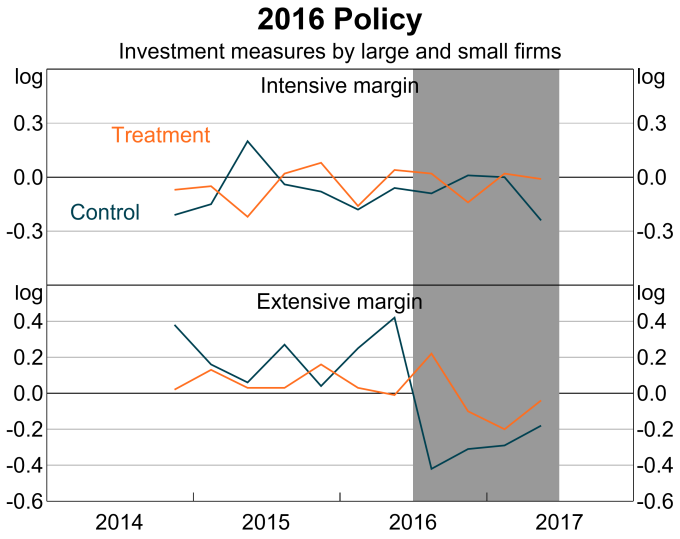
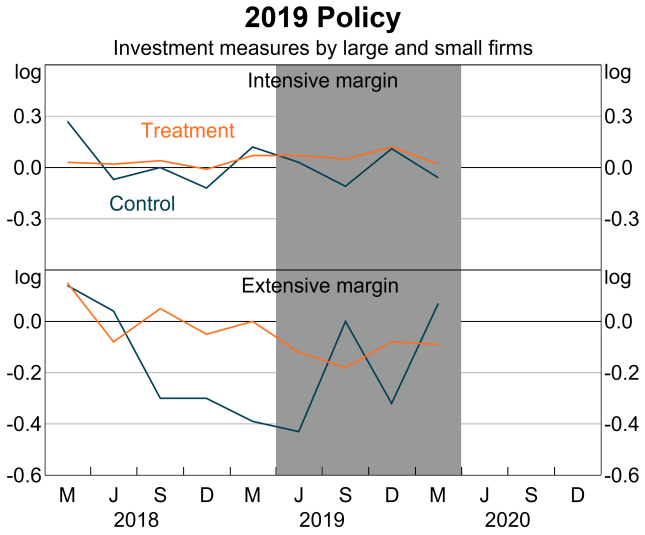


Figure 1.9: 2019 policy intensive and extensive margins



Turning to the regression results, some evidence suggests an effect at the extensive margin in the DD approach for all firms, though as noted, we are cautious in interpreting this result (Table 1.10). Moreover, as discussed below, these results might reflect the effect of coincident corporate tax cuts (section 1.7 below). Meanwhile the 2019 policy had no discernible effect on the intensive margin. The large negative effect on the extensive margin for unincorporated firms is imprecisely estimated and, as mentioned above, subject to substantial year-on-year volatility even in the absence of any policy changes.

We also show the RDD results for the 2016 policy in Table 1.11, with no evidence of an effect. However, firms are sparser around the $10 million cut-off, as reflected in the larger optimal bandwidth and smaller observation count. There may be too few firms to precisely estimate an RDD model for this policy.

The large negative coefficient in the June 2016 quarter, before the policy came into effect, could again reflect firms holding off on investment in anticipation of the policy. Although not statistically significant, the negative

[18] As noted above, the share of firms investing is much higher once we move to medium and larger firms. As such, the extensive margin becomes a less relevant metric.

Table 1.10: Difference-in-difference results: Medium-sized business measures

	Intensive margin			Extensive margin		
	All entities	Companies	Unincorps	All entities	Companies	Unincorps
Medium 2016	-0.0735	0.0166	-0.618**	0.295**	0.293**	0.295
SE	(0.120)	(0.139)	(0.260)	(0.122)	(0.142)	(0.178)
Observations	8663	6846	1772	18962	14062	4873
SBE 2019	0.0344	0.0837	-0.135	-0.289	-0.211	-0.784**
SE	(0.116)	(0.125)	(0.253)	(0.203)	(0.200)	(0.336)
Observations	7978	6732	1212	13646	11026	2593

Regressions include controls. Mining is excluded.
Cluster robust standard errors in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Table 1.11: RDD results: Medium 2016 policy

	Mar 2016	Jun 2016	**Sep 2016**	**Dec 2016**	**Mar 2017**	**Jun 2017**
All businesses						
Beta	0.099	0.293	-0.247	0.179	0.140	-0.140
Robust p-value	(0.78)	(0.14)	(0.36)	(0.49)	(0.47)	(0.49)
Bandwidth	2,156,505	2,296,991	1,702,082	2,275,956	1,970,100	1,451,920
Effective observations	1,154	1,224	1,039	1,218	1,140	957
Unincorporated						
Beta	-0.026	0.921**	-0.342	-0.186	-0.302	-0.561
Robust p-value	(0.79)	(0.03)	(0.60)	(0.75)	(0.62)	(0.19)
Bandwidth	1,497,854	1,765,229	1,969,430	1,850,328	2,080,014	1,673,069
Effective observations	293	331	326	333	338	334
Companies						
Beta	0.144	0.017	-0.272	0.330	0.401	0.0576
Robust p-value	(0.69)	(0.98)	(0.33)	(0.27)	(0.16)	(0.99)
Bandwidth	2,663,093	2,315,771	1,499,775	2,357,502	1,638,978	1,619,548
Effective observations	874	852	670	874	712	695

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

coefficients in the four following quarters suggest some investment increase for treated firms below the threshold. The sample sizes for these regressions are quite small. Again, there may be some weak evidence here for a response of unincorporated firms but there is no evidence of any impact for companies.

1.7 Robustness

In this section we discuss a number of threats to the identification of our models and conduct several robustness checks to assess the sensitivity of our findings and to aid in interpretation. These include the potential for firms to adjust their behavior to utilise the policy, and other policies that may have affected behavior.

The impact of corporate tax cuts

The 2015 and 2016 results may be confounded by corporate tax cuts implemented for the policy groups in 2015 and 2016. These were introduced coincident with the ITB, and had the same exact size cut-off for eligibility (see Tables 1.1 and 1.2).

In order to consider whether these policies had an effect, we exploit the fact that the ITB only applied to machinery and equipment, while the tax cuts lowered the cost of capital for any investment. We re-estimate the DD models, but for buildings and structures investment, as reported in the CAPEX data. While there is no response of this ineligible

investment to the GFC policy, we do see a significant increase for the 2015 policy at the intensive margin (Appendix D). This suggests the corporate tax cuts themselves may have increased investment. However, no evidence suggests an effect following the 2016 tax rate changes. We need to exercise caution in interpreting the RDD results for the SBE 2015 and Medium 2016 policies as the simultaneous nature of the tax cuts means we are picking up a combined effect of both policies.

Other policies

We know the corporate tax rate changes potentially affect our estimates of the 2015 and 2016 ITB policies but perhaps other policies also create differential incentives to invest at the threshold.

One possibility is that such policies pre-existed the ITB. This is unlikely to affect the DD results, as it will be captured by the pre-treatment difference in outcomes. But it could affect the RDD results. To consider this possibility we estimate the RDD for some quarters prior to the introduction of the policy. These are included in the tables which present the RDD results. No estimated difference in investment emerges at the threshold before the policies were in place, suggesting that pre-existing policies do not explain the results.

Another way to account for potentially confounding policies or factors that affect firms at the threshold is to look at other firm-level metrics that could be affected by those policies, but which should be less affected by the investment tax incentives. Table 1.12 examines firms' revenue and wages, focusing on quarters with evidence of a significant investment response. We find no evidence of a discontinuity in these other observables, providing further evidence that the effects we are finding reflect the investment policies.

Table 1.12: RDD results for revenue and wages

	Sep 2009	Dec 2015	Mar 2016	Jun 2016
Wages				
Beta	0.0386	0.0296	0.0700	0.0660
Robust p-value	(0.38)	(0.52)	(0.12)	(0.11)
Bandwidth	337,338	384,609	373,948	372,523
Effective observations	5,131	7,917	7,781	7,771
Revenue				
Beta	-0.017	-0.030	0.10	-0.026
Robust p-value	(0.67)	(0.12)	(0.84)	(0.32)
Bandwidth	350,983	288,230	404,467	307,524
Effective observations	5.599	7,899	9,517	8,224

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

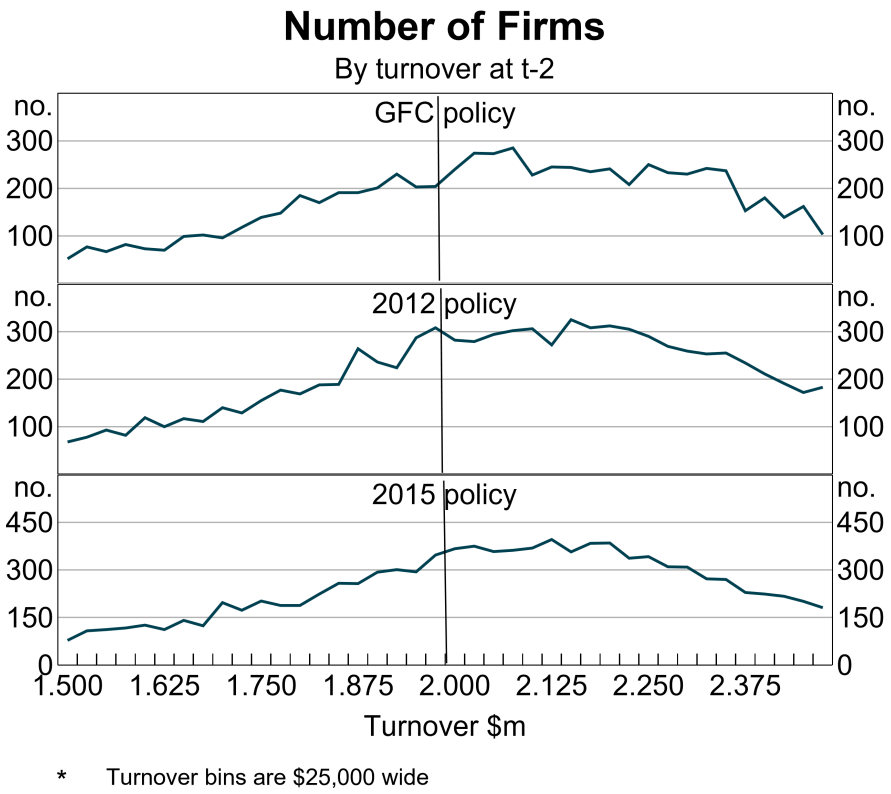
Validity tests - selection into treatment

One of the requirements for valid RDD is that businesses cannot manipulate the forcing variable, revenue, to change their treatment status. If businesses can select into treatment, the assumption that businesses just above and below the cut-off are identical would be violated. Businesses with a higher ex ante propensity to invest would have a greater incentive to select into treatment.

In our case, manipulation of the forcing variable – revenue measured over a year before the announcement of the differential tax break – is improbable. Consistent with this, no graphical evidence emerges of bunching of businesses just below the threshold (Figure 1.10). These graphical results are confirmed by the formal test proposed by Cattaneo et al. (2020).

The policy rules create an incentive for firms to manipulate their way into eligibility for the policy in a way that would remove them from our treatment and control groups. In particular, businesses with revenue above the cut-off in *t-2* and who forecast revenue just above the threshold in *t-1* or *t*, might have the incentive to manipulate their

Figure 1.10: Number of Firms By Turnover at $t-2$



revenue in year $t-1$ or t to qualify for the tax breaks. Recall that we dropped these businesses from our estimation sample–see section 1.5.

This could create a situation where our control group is comprised of firms with a lower propensity to invest than the true population of firms just above the threshold. The firms for whom manipulation into the policy is most valuable (those with the highest propensity to invest) are most likely to be absent from the control group.

We test the possibility of selection effects on the control group in two ways. One is to replace current investment in the regression with 2-year lagged investment. This test of a pre-determined co-variate should provide some sense of any inherent differences between the treated and non-treated groups.

Table 1.13 shows these results, focusing on the periods where the investment response was statistically significant. We find no evidence of a difference in the earlier investment propensity of firms either side of the threshold.

Table 1.13: RDD results using lagged investment

	Sep 2009	Dec 2015	Mar 2016	Jun 2016
Investment in *t-2*				
Beta	0.003	-0.065	-0.007	0.095
Robust p-value	(0.93)	(0.69)	(0.96)	(0.45)
Bandwidth	464,597	377,614	403,782	405,104
Effective observations	2,763	3,134	3,181	3,506

Robust p-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Still, we may be concerned that even if the earlier propensity to invest was the same, it may not be the case during the period of interest. As a further test, we rely on the assumption that businesses are only likely to be able to

manipulate their revenue to a certain extent. Businesses with revenue just above the threshold may be able to manipulate their revenue down, but businesses with revenue well above the turnover limit could not.

As shown in Rodgers and Hambur (2018) Figure 6, some evidence emerges that firms manipulated their sales in year *t-1* to qualify for the GFC policy. Specifically, a small spike appears in the number of firms with turnover just below the $2m in the 2008-2009 financial year, followed by a dip just after. It appears most of this came from firms with 'potential' turnover between $2m and $2.1m.

To account for this we follow Rodgers and Hambur (2018)) and re-estimate the model, only keeping firms with revenue in *t-1* or *t* more than 5 per cent above the threshold (equivalent to $100,000 for the $2m threshold). The logic is that it would have been more difficult for this subset of firms to manipulate turnover to be below the threshold. This reduces the concern that the control group only contains those firms that did not have the incentive to manipulate into the policy using turnover in *t* or *t-1*.

Table 1.14 shows the results, again focusing on the statistically significant periods. The results are quite similar, suggesting that manipulation is not driving the findings.

Table 1.14: RDD results - Donuts Manipulation Test Specification

	Sep 2008	Dec 2015	Mar 2016	Jun 2016
All firms				
Beta	-0.364*	-0.073	-0.500**	-0.197
Robust p-value	(0.05)	(0.79)	(0.02)	(0.35)
Bandwidth	306,648	426,061	298,216	522,424
Effective observations	1,584	2,763	1,969	3,014
Unincorporated				
Beta	-0.528*	-0.542**	-0.728**	-0.607**
Robust p-value	(0.06)	(0.04)	(0.02)	(0.03)
Bandwidth	315,977	335,454	311,429	386,911
Effective observations	705	1,198	1,010	1,208

Robust *p*-values in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Repeated treatment

As Australia has implemented a number of different ITB policies over recent years, one concern could be interaction between the various policies and overlap of the time periods covered by the policies. For example, firms that took up the GFC policy may have had less incentive to invest using the 2012 policy, if they had already made all the investment they desired.

We do see some evidence of overlap. For example, around half of the treated group in our GFC regressions were in our treated group for the 2012 policy. However, both our results and Rodgers and Hambur (2018) provide very limited evidence of bring forward over the 1-2 years following the GFC policy. We think the likelihood that this is driving our results for the 2012 policy is very low.

1.8 Conclusions

Various tax incentives have been provided to businesses in Australia over the past 15 years, both as a stimulus tool and as a structural tool to raise aggregate investment. Such incentives are inherently costly, making it important to understand whether they are effective in stimulating additional investment.

We evaluate seven policies over a 12 year period using difference-in-difference and regression discontinuity designs to identify the causal impact of investment tax breaks on firm investment. Our time period covers 'normal' economic

times, the GFC and the COVID pandemic period. This approach, of examining a range of policies, at different time periods in one country, allows us to draw conclusions about heterogeneous effects of investment tax breaks freed from issues of poor comparability often apparent in cross-country studies.

ITBs seem to be somewhat less effective in Australia, compared to many other countries. This appears related to the existence of dividend imputation, which lessens the value of the ITB to company shareholders and means that the policies mainly affect small unincorporated businesses. This is an important insight about the relationship between ITBs and other elements of the design of the overall tax system. Our finding is consistent with the old view of corporate finance, where firms fund themselves externally.

Overall, our results suggest the effectiveness of the policies studied is mixed at best, and probably highly dependent on the nature of the policy and macroeconomic conditions. In Australia, ITB policies as economic stimulus may be most effective during downturns which are driven by a shock to credit supply, rather than a sharp decrease in demand. ITBs appear to loosen cash-flow constraints for businesses in periods of credit dislocation. In 'normal' times they seem to have little effect. Policies targeted at smaller firms appear somewhat more effective: unincorporated businesses in particular are far more responsive. Policy uncertainty, reflected in frequent policy changes and uncertainty about the continuation of a policy, may undermine effectiveness.

Finally, while not the focus of our paper, we find evidence that corporate tax rate cuts led to an increase in investment, consistent with theory and previous empirical evidence from cross-country and other studies.

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Appendix 1.A Policy episodes

2008-09 GFC tax credit

The Government provided a temporary bonus income tax deduction for new investment in tangible depreciating assets undertaken between 13 December 2008 and 31 December 2009.

For small business entities (where turnover was less that $2 million), the Tax Break was 50% of their investment in an eligible asset undertaken on or before 31 December 2009. For all other taxpayers, the Tax Break was worked out using a rate 30% for investments committed to before 30 June 2009 and a 10% deduction for those committed to during the second half of 2009. The Tax Break can be claimed in the income year that the asset is first used or installed ready for use. The GFC tax break was in addition to any depreciation allowances for the asset in the year of investment and future depreciation deductions. New investment in relation to an asset needed to exceed a certain threshold before qualifying for the Tax Break. The new investment threshold is $1,000 for small business entities and $10,000 for all other taxpayers.

The investment tax break was announced in the Treasurer's Media Releases No. 141 of 12 December 2008 and No. 012 of 3 February 2009 and as part of the 2009-10 Budget of 12 May 2009. Amendments were passed in *Tax Laws Amendment (Small Business and General Business Tax Break) Act 2009*, which received Royal Assent on 22 May 2009. See `https://www.aph.gov.au/Parliamentary_Business/Bills_Legislation/Bills_Search_Results/Result?bId=r4094`.

For a pre-policy period over which we assess common trends we take the period from 1 July 2007 (21 June 2007 was the date of Royal Assent of legislation lifting the turnover threshold for small business concessions from $1 million to $2 million and simplifying a range of small business tax concessions under this one turnover test). The end of the pre-policy period is December 2008.

2012 Small business incentive

SBE taxpayers received an increase in the instant asset write off cost threshold from $1,000 to $6,500 for the 2012-13 income year and later income years. Simplification and consolidation of the small business depreciation pools were also implemented at the same time.

The change in asset threshold from $1,000 to $5,000 was announced on 2 May 2010 for the 2012-13 and later income years in response to the *Australian's Future Tax System* Review released in December 2009. On 10 July 2011, the Government announced that as part of the *Clean Energy Future* Plan the small business instant write-off threshold would be further increased from $5,000 to $6,500. The amendments were passed in the *Tax Laws Amendment (Stronger, Fairer, Simpler and Other Measures) Act 2012*, which received Royal Assent on 29 March 2012. SEE `https://www.aph.gov.au/Parliamentary_Business/Bills_Legislation/Bills_Search_Results/Result?bId=r4709`

With a change in government, and repeal of the Mineral Resource Rent Tax, the threshold was moved back to $1,000. The repeal of the MRRT was announced on 24 October 2013, and announcement of repeal of the higher threshold and related spending measures was announced on 18 July 2014. The changed in threshold was effective from 30 September 2014 with the passage of the *Minerals Resource Rent Tax Repeal and Other Measures Bill 2014*, which received Royal Assent on 5 September 2014. SEE `https://www.aph.gov.au/Parliamentary_Business/Bills_Legislation/Bills_Search_Results/Result?bId=r5327`

We take the date of announcement of the repeal of the MRRT as the end date of the policy since the original threshold increase was funded by the MRRT. Businesses would have anticipated repeal of other spending measures when the repeal of the MRRT was announced.

We define the policy period from 1 July 2012 to 31 December 2013 (quarter one 2012-13 to quarter two 2013-14). To look at pre-trends we take the period 1 January 2010 to 30 June 2012 (quarter two 2009-10 to quarter four 2011-12) which is the period after the end of the GFC investment incentive.

2015 Small business incentive

Small business entities (i.e, businesses with a turnover up to $2 million) were given an increased immediate deduction for a depreciating asset costing less than $20,000 from 12 May 2015 onwards. The temporary increase applied from 12 May 2015 until 30 June 2017. However, we only consider the policy through 31 December to avoid any potential influence from the introduction of the lower corporate tax rate for firms with turnover up to $10 million in May 2016.

The small businesses entities' tax rate was cut to 28.5% in 2015 by the *Tax Laws Amendment (Small Business Measures No. 1) Bill 2015*, which received Royal Assent on 22 June 2015. See `https://www.aph.gov.au/Parliamentary_Business/Bills_Legislation/Bills_Search_Results/Result?bId=r5465`.

2016 Small business incentive

The small business threshold was increased from $2 million to $10 million and the corporate tax rate was cut to 27.5% for businesses with a turnover less than $10 million from the 2016-17 income year onwards. This meant that business with a turnover up to $10 million could access instant write off provisions for assets costing up to $20,000. With the extension of that provision by 12 months, to 30 June 2018 (*Income Tax (Transitional Provisions) Act 1997*).

The tax cuts and change in the definition of small businesses were announced on 3 May 2016 as part of the 2016-17 Budget and implemented in *Treasury Laws Amendment (Enterprise Tax Plan) Act 2016*, which received Royal Assent on 19 May 2017.

For identification purposes we take 1 July 2017 as the end date of this policy. After this date, tax cuts (lowering the corporate rate to 27.5%) were implemented for businesses with a turnover of less than $25 million as per the *Treasury Laws Amendment (Enterprise Tax Plan) Act 2016*.

2019 Medium business incentive

The instant asset write off cap increased the maximum amount of allowable expenditure to $30,000 per asset between 2 April 2019 to 30 June 2020 (although this was overtaken by new provisions that commenced on 11 March 2020 and included businesses with a turnover of up to $50 million).

The corporate tax rate was cut to 27.5% for businesses with a turnover of less than $50 million from 1 July 2018 onwards, in accordance with legislation passed in 2016 (*Treasury Laws Amendment (Enterprise Tax Plan) Act 2016*).

We define the policy period as 2 April 2019 to 11 March 2020 (in financial year terms, quarter four of 2018-19 and the first three quarters of 2019-20). We define the treatment group as businesses with a turnover of between $10 million and $50 million for the 2018-19 financial year. We use businesses with a turnover of more than $50 million as the control group–see Table 1.3.

2020 Large business COVID incentive

The assets cost cap was increased from $30,000 to $150,000 and the turnover threshold was increased from $50 million to $500 million from 12 March 2020 to 30 June 2020. Proposal was announced in early March (either 12 March 2020, 18 March 2020 and 22 March 2020): (*Coronavirus Economic Response Package Omnibus Act 2020*). This policy was extended by six months to end on 31 December 2020 (announced in June 2020 and passed in (*Treasury Laws Amendment (2020 Measures No. 3) Act 2020*). However, this was overtaken by the expanded COVID temporary full expensing package, which started on 6 October 2020.

We define the policy period as 12 March 2020 to 5 October 2020 (in financial year terms, quarters two and three of 2019-20). We define the treatment group as businesses with a turnover of between $10 million and $50 million for the 2018-19 financial year. We use businesses with a turnover of more than $50 million as the control group.

2021 Very large business COVID incentive

The instant asset write off was expanded into Temporary Full Expensing (TFE). Under TFE, businesses with a turnover of less than $5 billion could deduct the full cost of eligible depreciating assets with no cap for assets first held, and first used or installed, between the 2020 Budget time (6 October 2020) and 30 June 2022. Loss carryback was also put in for entities with a turnover of less than $5 billion which allowed them to carry back a tax loss for the 2019-20, 2020-21 or 2021-22 income year and apply it against tax paid in a previous income year as far back as the 2018-19 income year. The policy was announced on 6 October 2020 and passed in (*Treasury Laws Amendment (A Tax Plan for the COVID-19 Economic Recovery) Act 2020*).

Businesses with a turnover of under $500 million were given a tax cut from 1 July 2021 with the new rate of 25%. This was in accordance with legislation passed in 2016 (*Treasury Laws Amendment (Enterprise Tax Plan) Act 2016*).

We define a policy period of 6 October to 30 June 2021, the latest observation in our data (the policy expired on 30 June 2023). We define a treatment group of businesses with a turnover between $500 million and $5 billion and use businesses with a turnover between $5 and $6 billion as the control group. These results are robust to changing the turnover bands.

Appendix 1.B Summary statistics

Table 1.15: Summary statistics for the $2m group (relevant for the 2009, 2012 and 2015 policies)

	Treated			Control		
	Mean	SD	Observations	Mean	SD	Observations
Investment ($'000s AUD)	156.68	1783.51	16,242	214.42	3305.30	5,052
Log odds investment	-1.40	0.87	75,542	0.27	1.75	10,123
Group turnover ($m AUD)	0.42	0.84	86,202	3.28	0.86	13,780
Employment	14.18	137.90	54,595	27.14	94.24	11,821

Note (a): Firms with group turnover under $2 million are included in the treated group. Firms with group turnover $2-$5 million are assigned to the control group.

Note (b) Only non-zero entries are used for investment.

Group turnover is the sum of the turnovers of all entities in the enterprise group to which a firm belongs.

Where a firm does not belong to an enterprise group, group turnover is equivalent to firm turnover.

Table 1.16: Summary statistics for the $10m group (relevant for the 2016 policy)

	Treated			Control		
	Mean	SD	Observations	Mean	SD	Observations
Investment ($'000s AUD)	224.42	2817.32	6,223	268.32	1323.15	3,678
Log odds investment	0.06	1.48	13,017	1.12	1.87	5,702
Group turnover ($m AUD)	5.10	2.31	14,959	14.28	2.82	6,529
Employment	54.28	275.22	12,802	82.32	139.00	5,745

Note (a) Firms with group turnover between $2-$10 million are included in the treated group, Firms with group turnover $10-$20 are assigned to the control group.

Note (b) Only non-zero entries are used for investment.

Group turnover is the sum of the turnovers of all entities in the enterprise group to which a firm belongs.

Where a firm does not belong to an enterprise group, group turnover is equivalent to firm turnover.

Table 1.17: Summary statistics for the $50m group (relevant for the 2019 policy)

	Treated			Control		
	Mean	SD	Observations	Mean	SD	Observations
Investment ($'000s AUD)	393.21	1956.87	6,953	531.55	1606.68	890
Log odds investment	0.84	1.60	11,151	2.29	1.94	1,118
Group turnover ($m AUD)	25.49	11.59	11,716	54.63	2.88	1,357
Employment	119.44	225.32	10,531	208.31	230.34	1,224

Note (a) Firms with group turnover $10-$50 million are included in the treated group. Firms with group turnover $50-$60 million are assigned to the control group.

Note (b) Only non-zero entries are used for investment.

Group turnover is the sum of the turnovers of all entities in the enterprise group to which a firm belongs.

Where a firm does not belong to an enterprise group, group turnover is equivalent to firm turnover.

Table 1.18: Summary statistics for the $500m group (relevant for the 2020 policy)

	Treated			Control		
	Mean	SD	Observations	Mean	SD	Observations
Investment ($'000s AUD)	1355.62	5467.85	16,619	3413.06	11531.34	1,082
Log odds investment	1.64	1.54	21,938	3.09	1.60	1,208
Group turnover ($m AUD)	196.90	120.30	22,231	549.30	28.83	1,337
Employment	412.37	470.99	20,751	771.23	920.41	1,305

Note (a) Firms with group turnover $50-$500 million are included in the treated group. Firms with group turnover $500-$600 million are assigned to the control group.

Note (b) Only non-zero entries are used for investment.

Group turnover is the sum of the turnovers of all entities in the enterprise group to which a firm belongs.

Where a firm does not belong to an enterprise group, group turnover is equivalent to firm turnover.

Table 1.19: Summary statistics for the $5b group (relevant for the 2021 policy)

	Treated			Control		
	Mean	SD	Observations	Mean	SD	Observations
Investment ($'000s AUD)	156.68	1783.51	2,079	214.42	3305.30	114
Log odds investment	-1.40	0.87	2,537	0.27	1.75	136
Group turnover ($m AUD)	0.42	0.84	2,582	3.28	0.86	154
Employment	14.18	137.90	2,553	27.14	94.24	151

Note (a) Firms with group turnover between $500 million to $5 billion are included in the treated group. Firms with group turnover $5-$6 billion are assigned to the control group.

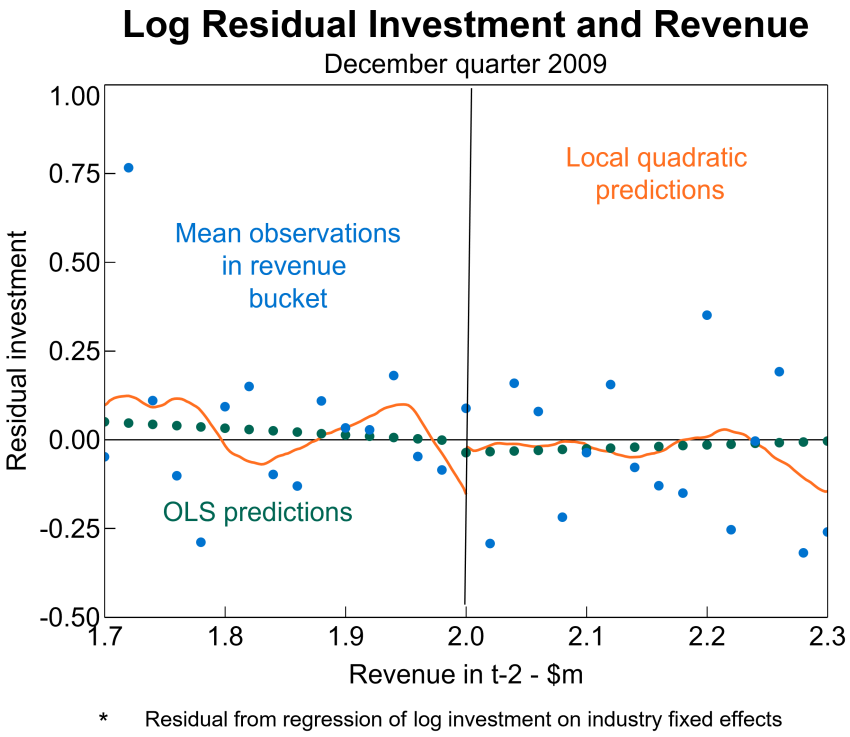
Note (b) Only non-zero entries are used for investment.

Group turnover is the sum of the turnovers of all entities in the enterprise group to which a firm belongs.

Where a firm does not belong to an enterprise group, group turnover is equivalent to firm turnover.

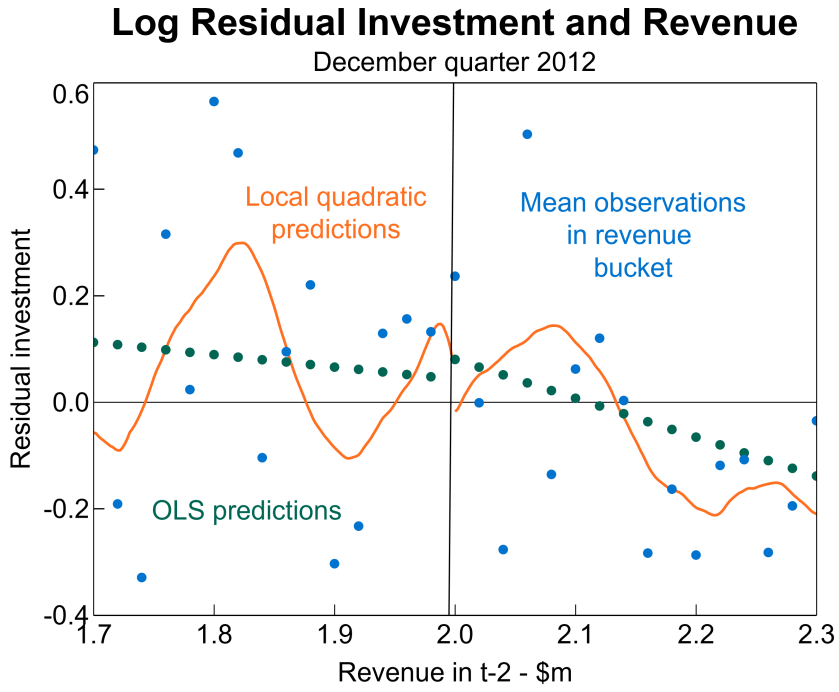
Appendix 1.C Additional RDD charts

Figure 1.11: Log Residual Investment and Revenue DEC 2009



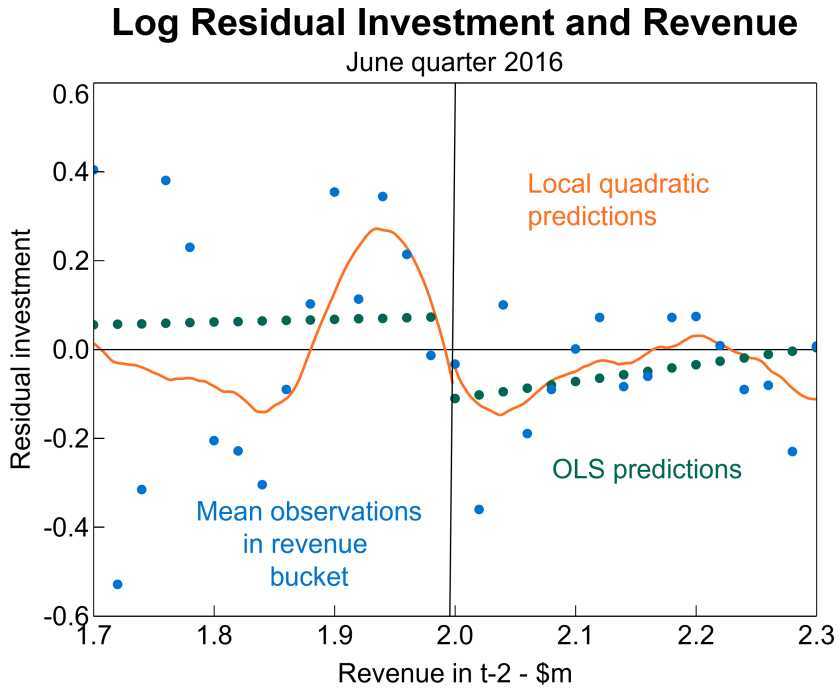
* Residual from regression of log investment on industry fixed effects

Figure 1.12: Log Residual Investment and Revenue DEC 2012



* Residual from regression of log investment on industry fixed effects

Figure 1.13: Log Residual Investment and Revenue JUN 2016



* Residual from regression of log investment on industry fixed effects

Appendix 1.D Testing for the effect of corporate tax changes

Corporate tax cuts

The 2015 corporate tax cut was a standalone measure announced at Budget on 12 May 2015 which gave incorporated businesses with annual turnover up to $2 million a 1.5 percentage point tax cut to 28.5 per cent. The Enterprise Tax Plan enacted a series of further tax cuts for small and medium sized companies across the ensuing six year–see Table 1.2. The tax cuts were announced as part of the 2015-16 Federal Budget.

To explore the possible effect of these tax cuts, we re-estimate the DD models using buildings and structures investment from the CAPEX data described above. This asset class is ineligible for the investment incentives that we study in this paper.

Looking at results for the GFC policy period, we can see there is no significant increase in investment in buildings and structures either on the intensive or extensive margins. There appears to be no complementarity between investment in these asset types (that is, increases in eligible machinery and equipment has no effect on investment in buildings and structures). This suggests that looking at buildings and structures can be a useful placebo test for other ITB policies.

In contrast, for the 2015, and to a lesser extent 2016, there is evidence of an increase in buildings and structures investment, suggesting that firms reacted to the corporate tax cuts.[19]. As firms appear to be responding to the corporate tax cuts, we should be cautious about interpreting our findings regarding the effects of the 2015 and 2016 ITB.

	Intensive margin			Extensive margin		
	All entities	Companies	Unincorps	All entities	Companies	Unincorps
GFC Policy 2009	-0.017	-0.074		-0.242	-0.182	-0.449
SE	(0.440)	(0.526)		(0.173)	(0.172)	(0.285)
Observations	1250	734		25880	13330	12518
2015 Policy	0.665**	0.829*		0.010	-0.157	0.0702
SE	(0.312)	(0.448)		(0.226)	(0.269)	(0.333)
Observations	1317	761		16808	9040	4008
2016 Policy	0.171	0.294		0.219*	0.156	0.277
SE	(0.323)	(0.351)		(0.125)	(0.134)	(0.181)
Observations	1897	1493		10612	7651	2908

Results exclude mining but include no controls due to small sample sizes.

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

Table 1.20: Buildings investment, excluding mining

[19]We do not show intensive margin results for unincorporated firms because very few firms make these investments.

Chapter 2

Tracking mergers and acquisitions using Australian administrative microdata

2 .1 Introduction

Australia has been rare among advanced economies in not having had a formal requirement for firms to pre-notify a merger or acquisition to a competition authority.[1] While this situation will change from 2026 when Australia introduces a formal obligation to notify, up until now notification has been purely voluntary. The absence of any formal reporting requirement has resulted in a lack of systematic data on M&A activity in Australia. This incomplete view of M&A activity has hampered Australia's competition authority, policymakers, and researchers from gaining a deeper understanding of the pattern of M&A activity and its effects on the Australian economy. For example, without systematic data it is difficult to assess how factors such as firm size and industry affect the pattern of M&A activity, let alone the impact of mergers on the employees, productivity and broader performance of the merging firms.

In this paper, we seek to address these gaps by building the first mergers and acquisitions database using Australian administrative datasets. The use of administrative data for research has expanded greatly in recent years with the increasing availability of powerful, linked government datasets. One goal of embarking on this project using administrative data, within the Australian Bureau of Statistics secure Datalab, is to enable future researchers to analyse the economic consequences of mergers and acquisitions. Such consequences, whether on productivity, innovation, labour movements or prices, are of central and significant relevance to a resilient, dynamic and productive private sector in Australia.

As mentioned above, this new database also comes at a critical juncture for Australia's merger system, as it moves from a voluntary to a mandatory and suspensory regime from 1 January 2026. This means mergers above designated monetary thresholds will be prohibited from proceeding without approval from the competition authority, and failure to notify such mergers will render them void. The specific thresholds set out in legislation are as follows:

1. Australian turnover of the combined businesses is above $200 million, and either the business or assets being acquired has Australian turnover of more than $50 million or global transaction value above $250 million.
2. A business with Australian turnover of more than $500 million buying a smaller business or assets with Australian turnover above $10 million.

We make use of these thresholds in our analysis below, allowing our new database to provide some early insights into how the new merger system may operate.[2] Similarly, our database can help inform these key policy settings going forward.

[1] 'Pre-notify' is used interchangeably with 'notify' in the merger context, with both referring to a requirement to alert the competition authority *before* a merger is completed. Merger control systems in many overseas jurisdictions are also 'suspensory' insofar as the merger cannot be completed until cleared by the competition authority.

[2] The new laws also include tailored notification rules for 'serial acquisitions', to deal with the strategy of larger businesses progressively accumulating market share via separate small transactions that would otherwise not be notifiable. The serial acquisition thresholds are not the focus of this paper's analysis but could easily be incorporated into future work.

The paper proceeds as follows. Section 2 .2 provides a short literature review and 2 .3 steps through the data and methodology for Australia and presents some preliminary analysis of mergers in Australia. Section 2 .4 presents estimates of the likelihood of becoming an acquirer or target and Section 2 .5 concludes and discusses next steps.

2 .2 Literature review

Our paper relates to previous overseas studies that seek to measure merger and acquisition activity using indirect methods in the absence of formal reporting requirements. These past studies have generally used one of the three methods to identify when a merger or acquisition has occurred: survey database, tracking worker flows or tracking entries and exits of businesses on business registers.

The first method uses survey or private sector databases on known mergers or acquisitions (such as Bloomberg or SDC Platinum investment banking deal activity database). However, private sector databases pose several limitations for research. Most notably, they fail to capture the full spectrum of mergers and acquisitions within an economy, often skewing towards publicly announced transactions. For instance, Sharma and Ho (2002) relies on a small sample of just 36 Australian acquisitions. Second, while these databases usually contain some firm-level and industry-level information, they do not have a full range of information on subsidiaries, workers, wages or prices. As a result, the prices, productivity and labour market impacts of firm mergers cannot be analysed.

The second method uses administrative data to identify restructures (including mergers) by tracking worker flows in a linked employee-employer dataset. This method can not only identify mergers, but improve overall administrative data quality by allowing researchers to identify firm restructures (Hethey-Maier and Schmieder (2013)). This method for identifying mergers is built on the assumption that workers from a target firm move together to the new acquiring firm. Since not all workers in a target firm may move (and the acquiring firm may rationalise the target workforce) a merger is usually taken to have occurred if a certain percentage of workers move together to a new firm. This method will normally exclude very small firms to remove the chance that natural turnover in these firms are erroneously identified as mergers. For example, Benedetto et al. (2007) and Geurts and Vets (2013) exclude firms with 5 or fewer employees.

Next, thresholds are applied to identify 'significant' worker moves. Previous methods have used either thresholds in the absolute number of employees moving together, or a percentage of the target firm or acquiring firm's workforce. For example, Benedetto et al. (2007) and Hethey-Maier and Schmieder (2013) use both measures, classifying a worker cluster transition to occur either where five or more workers move together between the firms and when 80% of employees from the target move to the acquirer. Similarly, Geurts and Van Biesebroeck (2014) uses a minimum cluster of three to five employees in addition to a set of percentage thresholds.

Worker transition percentages are also sometimes used to infer the nature of restructures beyond mergers, such as where a part of a firm is spun off to create a new firm. For example, Geurts and Vets (2013) links two firms using threshold worker flows and then identifies whether the firms are start ups, exiting or continuing firms, using the relative size of these flows. Geurts and Van Biesebroeck (2014) differentiates between mergers (where at least 50% of employees move to acquirer) and takeovers (where over 75% of workers move to the acquirer). Fackler et al. (2016) follows an approach used by Eriksson and Kuhn (2006) to identify start up firms, in which more than 50% of the initial workforce were employed together in the same firm in the year before, but only if this group of workers did not make up more than 50% of the predecessor firm's workforce.

Last, researchers have tracked business entries and exits using longitudinal linking of company records such as business registers or business demography statistics. This is more complete than the survey or private data. Depending on the jurisdiction and datasets, an identification number such as the business number can be changed for administrative reasons rather than an indication of true entry or exit. To eliminate 'false' entries or exits, researchers use probabilistic matching techniques to match similar characteristics such as name or addresses see (Geurts 2016).

This paper tracks mergers in Australia with administrative microdata, using the second and third of the methods outlined above - that is, by tracking both flows of workers and registries of tax consolidated groups. We also add a third, new method: tracking firms' lodgements of merger forms to the securities regulator. To track changes in company registers and firm lodgements, we will use data previously not available to researchers, on tax consolidated

groups and notifications to the securities regulator, the Australian Securities and Investment Commission (ASIC). We use private sector data sources to benchmark our results and analyse the factors that make it more likely a firm will be involved in a merger in a given year.

2 .3 Data and Methodology

We link employees to their employers using payrolls data and business datasets. Businesses are linked across all tax and other administrative datasets in Business Longitudinal Data Environment (BLADE) by their (anonymised) Australian business number (ABN). Furthermore, workers are linked to their employers by the anonymised ABN included in payrolls metadata.

First, using payrolls data, we track flows of clusters of workers moving from one firm to another within a short period of time. Each firm is tracked through its ABN. Worker flow data is expected to be a good measure of mergers because it includes:

1. Mergers by all business entity types (i.e. companies, trusts, partnerships); and
2. Mergers where significant assets are sold to another firm and a substantial number of workers move to the new firm.

Second, we track the movement of groups of companies between tax consolidated groups. Tax consolidation in Australia is where groups of wholly-owned firms are able to interact with the tax system as one entity for reporting taxable income and utilising tax losses. Where firms (or groups of firms) move between tax consolidated groups, we can infer that an acquisition or merger has occurred. A movement between tax consolidated groups is inferred where a firm nominates a new head company. At this point of nomination, we can infer that an acquisition has taken place as all equity interests in the entity must have been acquired by the new head company. Specifically, this method includes:

1. Mergers and acquisitions of companies within wholly-owned tax consolidated groups; and
2. Acquisitions of assets implemented through acquiring the company holding the asset within wholly-owned tax consolidated groups.

There should be little overlap between the labour flows method and the tax consolidation method. This is because under the tax consolidation method of tracking mergers, it is likely that the firm has stayed intact, and has been added to the tax consolidation group as a new subsidiary member. In contrast, under the labour flows method, the fact that a substantial percentage of employees have moved to another firm implies that the target firm has been wound down.

Last, we track forms submitted to ASIC signaling a takeover or a scheme of arrangement, which are both methods under which mergers may occur in Australia. These three methods are outlined in more detail below.

It is useful to note here that there are some limitations in using these methodologies in tracking merger activities. For example, we cannot capture cases where there has been an acquisition of business operations through the purchase of buildings, equipment, leases and intellectual property that are sold to another entity but where no/few workers move with the assets. For example, we can only capture the case where a firm disposes of its logistics operations to another entity by selling all its capital equipment and client accounts when many staff move to the new firm with the equipment. Nor will our methodology capture the instance where control of a firm is acquired by another entity through acquisition of majority shareholding/special voting rights. Looking at these other forms of change in control of a firm's operations would be a useful area of future research.

Tracking employee flows

Using payment summaries from the Person Level Integrated Data Asset (PLIDA) linked with firm-level data in the Business Longitudinal Data Environment (BLADE), we link all employees to their employers in Australia over the period 2000-2020. We then identify all worker transitions (ie, when a worker moves employers) and apply the

following rules: we keep all movements where a worker was at a new firm in year t but not at $t-1$; and where workers are at a new firm in year $t+1$ but not in $t-1$.

To focus on mergers, rather than normal job transitions, we require 50% or more of all employees in a target firm to move to the acquiring firm within the year. In line with the literature, we also remove cases where target firms have fewer than 10 employees to limit the possibility that we are picking up movements of a handful of workers in job transitions unrelated to mergers. We remove corporate restructures, where both acquiring and target firms belong to the same Enterprise Group (EG). An EG in BLADE is a group of related businesses that are usually part of a wholly-owned or otherwise controlled group. These filters give us the full sample of all possible mergers, as indicated by the Full sample line in Figure 2 .1.

We attempt to remove phoenix firms by requiring that the acquiring firm must have existed in $t-1$. A firm may phoenix when it ceases operations and restarts under another business, without a substantial change to its workforce. This can also occur for reasons such as change in business type (eg, going from partnership to company). However, requiring that firms must exist in $t-1$ potentially removes mergers that are implemented by way of a new special purpose vehicle (SPV), or where two firms merge into a new entity. We address the latter by adding back in cases where two firms appear to be acquired by one new firm. Further work could address the use of SPVs, potentially by requiring that the EG existed in $t-1$, not the ABN, as SPVs are primarily used by large entities for complex/large acquisitions.

One limitation of this method is, as noted above, we cannot track mergers where assets move from one business to another but very few workers move with them. For example, a business operation may be sold where only the assets are moved, but the staff are retained by the parent company or are let go. In this case, we cannot track the merger as assets are not tracked in our dataset.

Using this methodology, we find that there were around 1,000 mergers each year from 2003-2018. Figure 2 .1 shows three series. First, it shows the counts of activity where at least 50% of workers have moved to a new entity between one year and the next (labeled as 'Full sample'). Imposing the filter that the new firm must exist before the labour movement gives us the second series, labelled 'Pre-exist.' Last, adding back in our suspected cases of special purpose vehicles gives us the final estimate of mergers and acquisitions using this method. Figure 2 .1 shows that there was a period of relatively robust mergers activity in the early to mid 2000s, with a spike in 2008 of around almost 2,000 acquisitions. Mergers activity dropped off to around 1,000 acquisitions in 2009. Activity has been slowly rising over the past decade, although mergers activity remains lower than in the period before 2009.

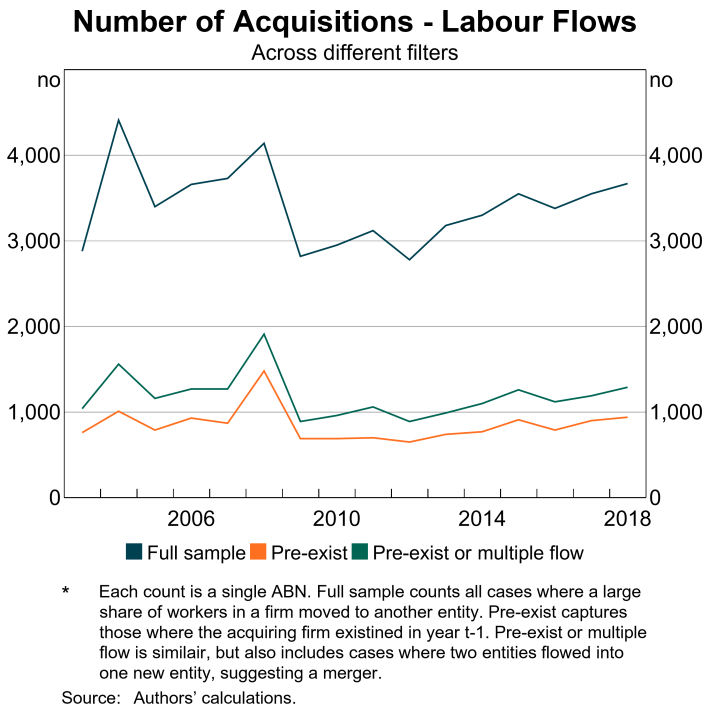


Figure 2 .1: Number of mergers using different filters

Tracking movements between tax consolidated groups

The tax consolidation regime in Australia allows wholly-owned entities to be treated as a single entity for taxation purposes. Entities that are wholly-owned by a foreign parent entity can form a multiple entry consolidated group. In both cases, a head entity must be nominated as the ultimate holding company for every member of the group. We can therefore infer an acquisition has taken place when an entity changes its nominated ultimate holding company and consolidated group identifier in its tax records.

Specifically, we define a merger as having potentially occurred where, in a financial year:

1. an ABN is currently a member of a consolidated group;
2. the ABN transferred from a different consolidated group, and
3. the time difference between the end date at the previous consolidated group and the start date at the new consolidated group is less than 30 days.

One limitation of this method is that it will miss mergers where the target firm is not already part of a consolidated group. While it is possible to track firms that enter a consolidated group, it is not possible to determine if this event represents the entry of a firm already owned by the group or mergers activity. As a result, we limit our mergers counts to include only those cases where a firm is already part of a consolidated group and changes its nominated head company.

We find around 2,000 ABNs switching between tax consolidated groups over the past 20 years (Figure 2 .2, with a spike of activity in the mid-2000s, echoing the spike we saw in the labour flows charts. This suggests there may have been significant restructuring around this time that resulted in ABNs being acquired but also workers moving between entities. We also find something interesting: a third to a half of all ABNs that are switching between consolidated groups do not post a turnover in the tax system, and many do not have payment summaries associated with them, indicating that these firms do not have any employees. This may be because these entities are vehicles for holding assets such as buildings, plant or intangible assets such as options, leases or intellectual property assets.

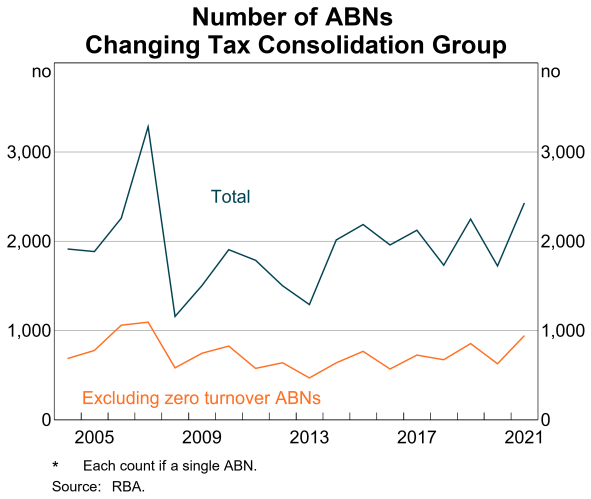


Figure 2 .2: Number of ABNs moving between consolidated groups

Looking at the ABNs we further find that *groups* of ABNs move together from one consolidated group to another. Aggregating and tracking firms that move together may be a more accurate way to track mergers than simply counting the ABNs separately. This is because the firm grouping may represent one arm of economic activity - where plant and buildings are owned by one ABN, the intellectual property by another, and workers attached to yet another firm. It can also more accurately represent the overall financing effort or size of the 'deal' that the acquirer undertakes. For these reasons, we take a group of ABNs moving between groups as one merger and the preferred measure for tracking mergers between consolidated groups.

Overall, grouping the ABNs that are moving together, plus adding singleton firm moves, we find that over the past 20 years, between 300 and 400 groups of ABNs moved between tax consolidated groups. Figure 2 .3 shows that the period of relatively robust activity in 2008 was followed by a sharp drop off in 2009, again echoing the mergers activities we saw in the labour flows method. Activity has been slowly rising since 2010, recovering back to around 400 mergers per year by the end of our data.

Interestingly, some acquisitions are of groups of ABNs that post zero turnover, so potentially holding assets such as buildings or intellectual property. The counts have been relatively stable, with around 150 groups of firms every year posting zero turnover in the tax system.

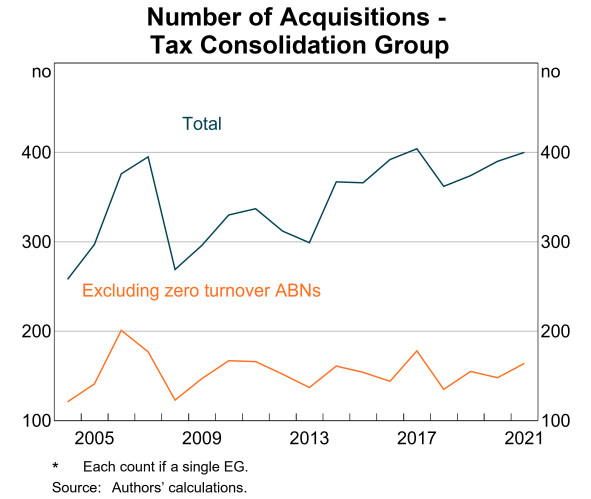


Figure 2 .3: Number of acquisitions by Enterprise Group

Takeovers and schemes of arrangement

The Australian Securities and Investment Commission (ASIC) requires several forms to be lodged when one firm conducts a takeover of another firm. These forms are related to takeover bids and conditions related to the takeover operation. These forms were integrated into BLADE using their ABNs, making this data available to researchers for the first time.

There are two types of takeover bids: an off market bid (which may offer cash or other consideration, may be subject to conditions, and may be for 100% of the target securities or a specified proportion of each target security holder's securities); and a market bid (which must be an unconditional cash offer). Virtually all takeover bids are off-market bids because of the ability to include conditions (such as 'defeating conditions' which ends the takeover bid if conditions are not met). Another way that firms may merge is through a scheme of arrangement, which is a shareholder and court-approved statutory arrangement between a company and its shareholders that becomes binding on all shareholders. Members of a scheme lodge a court order document approving the scheme, which we use to identify those entities involved in a scheme. We focus on the forms submitted by the acquirer (which comprise almost all the form types) and ignore forms submitted by the targets to avoid double counting. The relevant forms are detailed in Appendix A.

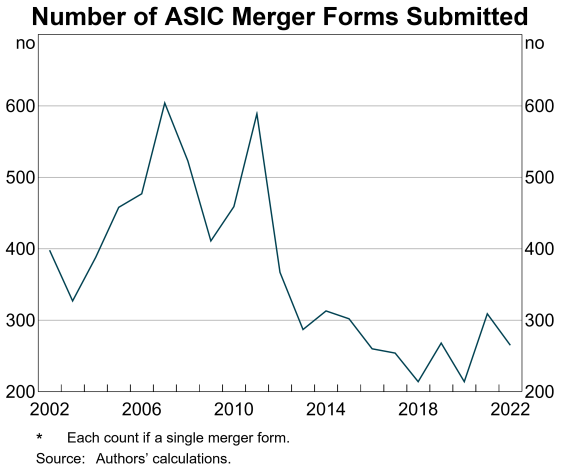


Figure 2 .4: ASIC forms submitted

Adding this method allows us to identify the firms undertaking mergers but does not accurately allow us to identify the number of mergers taking place. This is because each merger/takeover is likely to have a number of forms submitted during execution, with the combination of forms specific to the circumstances of the transaction. We see a spike in the number of acquiring firms in 2008 and 2009, echoing the analysis presented above using the labour flows and tax consolidated groups method. Interestingly, we see another spike in 2012 and 2013, after which the number of acquiring firms stabilises to around 50 firms each year.

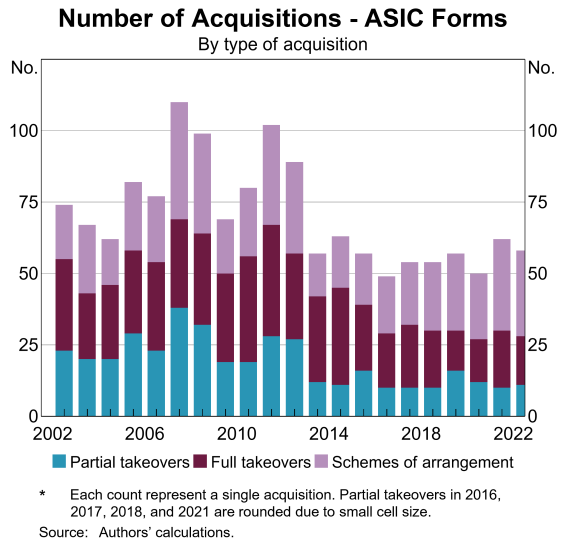


Figure 2 .5: Count of firms lodging takeovers and schemes forms
Note: Partial takeovers in 2016, 2017, 2018 and 2021 have a count of 10 or less and are rounded to 10 to prevent identifiability of firms.

Overlaps between methodologies and benchmarking

The method of tracking ABNs between consolidated groups is an almost-perfect complement to the labour flows methodology. Under the labour flows method outlined above, if a substantial proportion of workers have moved to a different ABN, it is likely that the target firm (or all of its assets) has been acquired and the firm possibly wound down. If, in contrast, an ABN moves between two consolidated groups, it has stayed intact in its legal form and we would not expect to see a high proportion of its labour moving to a new ABN. In the very few cases where the two methods overlap, it is possible that a company has been acquired, and some of its operations rationalised inside the consolidated group, resulting in a large proportion of workers moving *and* the ABN remaining intact. There are also very few overlaps between the labour flows methodology and the mergers identified through the takeovers and schemes of arrangement method. Over the 20 years of data, there are under 20 instances of overlap for each of these additional methods in tracking mergers.

To benchmark our database we compare the mergers counts extracted from our labour flows and tax consolidated groups method with mergers announcements in Bloomberg.[3] We compare total counts of mergers averaged over five years because our administrative database uses secure, anonymised firm-level data that preclude identification.

We use the value of a 'deal' from the Bloomberg database to categorise the merger targets by size of acquisiton. To derive something similar to a deal value in our mergers database we use fields in the tax administration dataset. In particular, we derive deal values as being over a certain deal threshold in the following way:

1. If turnover of the target firm is above the threshold, the deal value is taken as at least equivalent to the turnover.
2. We add target firms where the combined income and financial assets of the target entities are over the threshold.

The Bloomberg dataset indicates that many of the largest transactions involve acquisitions of the Australian branch or subsidiary of multinational entities where the reported 'deal value' is very large and likely involve assets and entities held offshore and not within the Australian tax system. Since Bloomberg picks up global deal values, and not just the value of Australian-based acquisitions, we must take a position on targets that are part of global groups. To do this, we identify targets that have entries in tax fields that suggest they are part of a multinational entity ('foreign flags'). These are then categorised as having the highest deal value. The 'foreign flags' we use are:

[3]We do not add the final method which uses ASIC form lodgements into the benchmarking analysis as we cannot trace the merger target (and therefore we cannot trace the value of the 'deal') using that methodology.

- Ultimate holding country code not Australia
- Attributes foreign income to a listed country
- Has overseas interest expense or overseas royalty expenses
- Value of overseas transaction $>$ \$2m

For mergers derived through the tax consolidation group switches methodology, we add the turnovers and assets of the *groups* of entities moving between consolidated groups. We also look to see if any of the entities moving have a 'foreign flag' indicating that they are part of a larger, global business grouping and assign these to the largest deal category.

Table 2 .1 shows annual counts averaged over the 2014 to 2018 financial years extracted from both Bloomberg and our mergers database. The counts indicate that our mergers dataset (using only labour flows and tax consolidation methods) is picking up almost 300 additional mergers compared to the Bloomberg database. The number of mergers picked up under the two sources converge as the deal value rises, especially for the largest deal values of \$100 million and over. This is consistent with expectations: private sector databases are most likely to track and report on large, publicly-announced deals that have the potential to move markets, but may have incomplete coverage of small and mid-sized transactions.

Deal Value	Mergers database	Bloomberg
All	1,546	1,274
\$20m and over	347	373
\$100m and over	191	193

Table 2 .1: Counts by deal value

Serial acquisitions

Unlike private sector databases such as Bloomberg, our mergers database enables a range of further questions to be addressed using the rich cross-linked data in the BLADE and PLIDA environments.

As an illustration, we present initial results for 'serial acquisitions' (or 'creeping acquisitions') where an acquirer makes numerous small acquisitions in the same market over time that cumulatively lead to a significant increase in market share. A serial acquisition strategy can allow an acquirer to avoid review by competition authorities as each individual acquisition is too small to be detected and/or trigger statutory thresholds for notification.

We start by looking at some aggregate measures of serial acquisitions. To do this we simply look at how many identified acquisitions each acquirer has over the sample, where we treat multiple acquisitions occurring in the same year as one to limit issues around several entities being acquired as part of the same deal. We can see that around 10 per cent of acquirers have more than one acquisition, with a number having several across the sample (Table 2 .2).

	Labour Flows Method	TCG Method
1	8,170	3,140
2	720	240*
3	180	-
4	70	-
5+	110	-

* Includes cases with more than 2 acquisitions.

Table 2 .2: Number of Acquisitions per Acquirer

While the aggregate numbers are useful to get a sense of these outcomes, we may be particularly interested in cases where acquisitions are in the same industry, as these cases may be more concerning from a competition dimension. And even more so where there are several such acquisitions over a number of years (ie. creeping acquisition).

We create a measure of serial acquisitions as follows. First we use the mergers identified through the labour flows methodology. This is because we can link the acquirer and target under the labour flows method (unlike the ASIC method) and the entity being acquired is likely to be an entity with business operations (as it holds the payrolls of staff, unlike the tax consolidated method where groups of related entities may move together, with some firms having zero turnover). Then we identify potential cases of serial acquisitions by selecting labour flows where:

- the acquiring ABN and target ABN share the same 4-digit ANZSIC class ('same-industry')
- the acquirer has made same-industry acquisitions in a single ANZSIC class in at least 3 years during the period 2003 to 2018. These years need not be consecutive.

We find that around 7% of acquisitions are same-industry, serial acquisitions. This compares to around 40% of all flows being same-industry acquisitions. Of the 61 serial acquirers across these top ten ANZSIC classes, around 40% were in the top 10 of their ANZSIC class by turnover in the year of the acquisition.

Table 2 .3 shows the ANZSIC classes with the highest incidence of these same-industry, serial acquisitions, based on the number of years where acquisitions occur, summed over acquirers. It is interesting that the top four serial acquisition industries are in care and medical services. One direction for future research would be to explore how such serial acquisitions affect market concentration, prices and wages in these industries.

Rank	ANZSIC class
1	Q-8710-Child Care Services
2	Q-8601-Aged Care Residential Services
3	Q-8511-General Practice Medical Services
4	Q-8531-Dental Services
5	G-4110-Supermarket and Grocery Stores
6	M-7000-Computer System Design and Related Services
7	H-4512-Takeaway Food Services
8	G-4271-Pharmaceutical, Cosmetic and Toiletry Goods Retailing
9	H-4400-Accommodation
10	H-4520-Pubs, Taverns and Bars

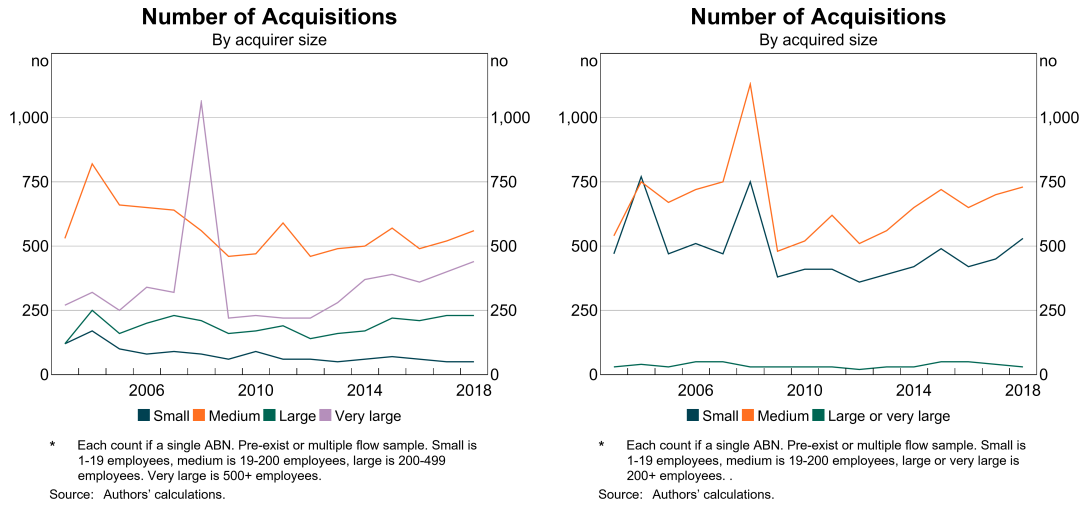
Table 2 .3: Top 10 ANZSIC classes for same-industry, serial acquisitions by number of years with acquisitions

Merger counts by year

Quantifying merger counts is useful for a range of policy purposes, such as analysing how many mergers might be reported under a mandatory reporting regime, or the resourcing needed for regulators to review mergers at different firm size thresholds. Note that these counts do not necessarily equate with the number of firms undertaking mergers since one firm or business group may undertake more than one acquisition in a year.

To look at the number of mergers that are occurring in each year, we use mergers identified under the labour flows method as it provides the clearest indication of merger counts. While the ASIC and tax consolidated groups methods both identify possible mergers, they are excluded from the firm-level analysis for two reasons. First, while we can identify which firms are submitting mergers-related forms to ASIC we cannot know how many mergers are taking place as we cannot currently group these forms together for each merger. Second, groups of entities seem to be moving between head companies in the tax consolidation group method, with some posting nil turnover and employment, and likely holding only assets. In these cases it is difficult to discern how many mergers have taken place.

Figures 2 .6a and 2 .6b decompose acquisitions based on the size of the acquirer and target firm. We can see that most target firms are medium-sized businesses, while acquisitions are disproportionately made by very large firms (who account for less than 1% of the universe of firms). After a large spike in activity in 2009 by large acquirers (related to the health sector) merger activity stabilised for all sizes of acquirers for a run of years before slowly increasing after 2013.



(a) Acquirers

(b) Targets

Figure 2 .6: Counts by size by year

2 .4 Odds of being an acquirer or target

What are the key firm-level factors that affect the likelihood of being involved in a merger, either as an acquirer or a target? While the overseas literature is well-developed on this issue, studies in an Australian context are rare owing to the data limitations discussed above. For example, overseas analysis has shown that firms may seek to increase innovation or patent stock (Mahdiyeh and Moshiri (2019)), relieve financial frictions in target firms, especially when the target firm is relatively small (Erel et al. 2015), or be driven by cyclical technological or industry shocks (Martynova and Renneboog (2008)). Managerial hubris or misstep may also be a factor: Martynova and Renneboog (2008) shows that takeovers towards the end of each cyclical wave of mergers are usually driven by non-rational, frequently self-interested managerial decision-making. The motivation for mergers can also be highly industry-specific and strategic within a regulatory environment: for example, the desire to obtain 'too-big-to-fail' status may motivate US banking mergers (DeYoung et al. 2009).

Our dataset is well-placed to explore questions relating to entity size, productivity, broader performance measures including profitability, and more niche issues such as the role of intellectual property.[4] As detailed below, we use this dataset to quantify how these characteristics affect the likelihood of a business being involved in at least one merger in a given year, providing separate estimates for acquirers and targets.

To do this, we need to decide how to treat multiple firms within the same enterprise group. If the firm is part of an enterprise group, we proceed by aggregating all variables discussed below at the enterprise group level. Where a firm is not a member of a enterprise group, it is treated as a one-firm enterprise group and all variables are constructed at firm-level.

This means that an acquisition by any firm within a broader business group (regardless of its share of the group's activity) is taken as an acquisition by the group as a whole. This is consistent with the notion that strategic business decisions are made at the enterprise group level.

In addition, where a target firm is part of a larger enterprise group, the target is interpreted as a large enterprise group being involved in a disposal of a firm via a merger. Again, this is because the disposal of a firm (regardless of size) can be taken as a strategic decision by the enterprise group acting as one economic unit.

We use the mergers as measured by the labour flows and ASIC methods outlined above, linked in BLADE by their ABNs. We do not include mergers as measured by movements between tax consolidated groups for this analysis. This is because movements between these tax-consolidated entities consist of groups of entities moving together,

[4]This analysis has focused on a subset of data currently available in BLADE. However, further avenue of research will become possible as the ABS adds new data modules into BLADE in areas such as managerial skill and corporate board membership.

some of which post no income or employees. In this case, performance measures cannot be calculated or may not reflect the true nature of the acquisitions even where they can be calculated.

We explore the impact of enterprise group size, measured by both employment and turnover, on the likelihood of being an acquirer or target. An examination of the raw data indicates that the percentage of firms/enterprise groups making at least one acquisition in a financial year rises monotonically with size (consistent with Figure 2 .6a), with around 8% of all enterprise groups with a turnover of over $500 million tagged in the dataset as acquirers, compared to around 5% in the $200 to $500 million turnover bucket and 2% in the $50 to $200 million turnover bucket. Less than 1% of firms in the smallest turnover buckets (under $10 million and between $10 to $50 million) are acquirers.

In contrast, the pattern for targets is less clear, with a more even distribution of target percentages among the mid and higher turnover buckets. The results for mid-sized firms is generally consistent with Figure 2 .6b. However, since we are looking at targets at the enterprise group level, results at the higher turnover bucket should be interpreted as a disposal of potentially smaller firms by large enterprise groups.

We also include measures of firm/enterprise group performance, measured by productivity and profitability. Productivity (calculated as value added divided by full-time-equivalent employment) and profitability (profitability is calculated as income divided by expenses) are constructed using variables from the business income tax records in BLADE.[5] We use a 3-year average of these variables to abstract from volatility, and to account for the fact that sustained profit and productivity performance may be required for a firm to decide to undertake a merger.

To explore the role of intellectual property, we include variables for whether the firm/enterprise group involved in the merger holds one or more patents and trademarks. We use trademarks and patents registered by each firm as recorded by Intellectual Property Longitudinal Research Dataset (IPLORD).

Finally, we include industry and year effects. We control for industry effects by including dummies for the 19 ANZSIC divisions. For enterprise groups containing multiple firms in different industries, we assign the most common ANZSIC division to the entire group. To account for macroeconomic effects including the year-to-year volatility in M&A activity, we include year dummies.

Formally, we estimate a logistic regression where the dependent variable is equal to 1 if the enterprise group i engages in at least one acquisition or is a target in a year t and 0 otherwise. We include firm size, whether the enterprise group held at least one patent or registered trademark as well as profitability and productivity and year fixed effects (δ_j). Standard errors are clustered at the firm/enterprise group level and we estimate both with and without industry dummies (γ_{it}).

$$\begin{aligned} log\left(\frac{Pr(P_{it}=1)}{1-Pr(P_{it}=1)}\right) = = \beta_0 + \beta_1 \text{size}_{it} + \beta_2(\text{productivity}_{it}) + \beta_3 \log(\text{profitability}_{it}) \\ + \quad \beta_4 \text{trademark}_{it} + \beta_5 \text{patent}_{it} + \gamma_{it} + \delta_j + \varepsilon_{it} \end{aligned} \tag{2 .1}$$

Acquirer results

The likelihood of being an acquirer rises monotonically by size, measured both by employment and turnover. Compared to enterprise groups with a turnover of less than $10 million, firms/enterprise groups in the next turnover bucket are 6 times more likely to be acquirers. This increases to 15 and 28 times more likely for firms in the $50 million to $200 million and the $200 million to $500 million turnover buckets. The largest enterprise groups with a turnover of more than $500 million have the highest odds of being an acquirer - they are 48 times more likely to be acquirers compared to the reference group of firms/enterprise groups with a turnover of less than $10 million. This monotonic increase in the odds of being an acquirer is also apparent when we measure size using employee headcounts instead of turnover. Results controlling for industry show similar (under headcount measures) or stronger (under turnover measures) relationships between the size of an enterprise group and the odds of it being an acquirer. The results also indicate that firms holding at least one registered trademark are more likely to be acquirers.

[5]Value added is calculated as income minus expenses plus depreciation, wages, interest, super, bad debts and rent.

Profitability does not affect the odds of being an acquirer (omitted from results). The productivity results range from higher productivity leading to a slightly lower likelihood (under turnover measures of size) to a slightly higher likelihood (under headcount measures of size).

Enterprise groups holding at least one trademark are around 1.6 to two times as likely to be an acquirer, with slightly smaller odds after controlling for industry. The existence of a patent does not seem to increase the odds of an enterprise group being an acquirer.

Australia's new mandatory merger regime will require notification where (a) the acquirer has a turnover above $200 million, and the target has Australian turnover of more than $50 million; and (b) a business with Australian turnover of more than $500 million and the target has a turnover above $10 million. These results indicate that the threshold at $200 million would capture firms most likely to be acquirers. Future research could explore whether mergers in this segment tended to generate more or less desirable impacts on the market and performance of the merged business.

	No Industry	With Industry	No Industry	With Industry
$10m to $50m	6.301***	6.862***		
	(0.194)	(0.234)		
$50m - $200m	15.16***	16.72***		
	(0.719)	(0.862)		
$200m - $500m	28.88***	32.25***		
	(2.153)	(2.535)		
$500m+	48.45***	54.62***		
	(4.371)	(5.224)		
21-200 employees			5.914***	6.006***
			(0.216)	(0.220)
201-500 employees			32.79***	32.12***
			(0.000394)	(0.000376)
501+ employees			88.36***	83.80***
			(5.151)	(5.097)
Patent	1.031	1.089	1.138	1.188*
	(0.0933)	(0.0988)	(0.101)	(0.105)
Trademark	1.879***	1.722***	1.601***	1.590***
	(0.125)	(0.118)	(0.0983)	(0.102)
Productivity	0.918***	0.921***	1.204***	1.177***
	(0.0119)	(0.0123)	(0.0231)	(0.0231)
Observations	2,307,420	2,307,420	2,339,794	2,339,794
Year fixed effects: YES				

Table 2 .4: Likelihood of a firm being an acquirer (odds ratios

Target results

Looking at the target results, we find something interesting: larger enterprise groups are more likely to be involved in mergers than smaller firms, indicating that large entities are potentially disposing of firms and subsidiaries to other entities through mergers. Compared to enterprise groups making less than $10 million, enterprise groups with a turnover of more than $500 million are around twice as likely to have been involved in a merger as a target. Under the headcount measures, enterprise groups with more than 500 employees are around 1.6 times more likely to be involved in a merger either through the disposal of one or more subsidiaries or itself merging.

The category of smaller mid-sized firms/enterprise groups are the next most likely to be involved in a merger, with firms/enterprise group with a turnover of between $10 million and $50 million 1.39 times more likely to be targets in a merger than firms/enterprise groups with a turnover of under $10 million. This pattern also holds when we measure size by employment, with firms/enterprise groups with 21 to 200 employees 1.6 times more likely to

be targets in a merger. The estimated odds for the smaller end of mid-sized firms rises slightly once we control for the industry (to 1.46 times more likely under the turnover measure of size, and 1.62 times more likely under the headcount measure of size). Finally, targets are more likely to have trademarks (significant at 1% under the headcount measure of size) and, under all specifications tend to be slightly less productive (perhaps partly reflecting large enterprise groups need to restructure by disposing of businesses).

The proposed thresholds in the new mergers regime focuses on targets with Australian turnover of more than $50 million and targets with a turnover above $10 million. Our results imply that focusing on the $10 million and above group would be appropriate to capture those entities most likely to be targets in a merger.

	No Industry	With Industry	No Industry	With Industry
$10m to $50m	1.392***	1.458***		
	(0.0398)	(0.0428)		
$50m - $200m	1.231***	1.251***		
	(0.0882)	(0.0903)		
$200m - $500m	1.316**	1.318**		
	(0.183)	(0.185)		
$500m+	2.097***	1.961***		
	(0.0270)	(0.0279)		
21-200 employees			1.579***	1.615***
			(0.0270)	(0.0279)
201-500 employees			1.160**	1.067
			(0.0809)	(0.0744)
501+ employees			1.588***	1.332***
			(0.143)	(0.120)
Patent	0.787	0.832	0.854	0.924
	(0.136)	(0.146)	(0.145)	(0.159)
Trademark	1.129	0.997	1.601***	1.590***
	(0.114)	(0.103)	(0.128)	(0.127)
Productivity	0.911***	0.849***	0.944***	0.878***
	(0.0102)	(0.00842)	(0.0109)	(0.00901)
Observations	2,307,420	2,307,420	2,339,794	2,339,794
Year fixed effects: YES				

Table 2 .5: Likelihood of a firm being a target (odds ratios)

2 .5 Conclusion

Mergers and acquisition research in Australia has long been hampered by shortcomings in data availability. Previously available data sources have not had full financial details of the transacting parties, nor has it previously allowed linking with the employees in each of the firms. In this new mergers and acquisitions database we present a methodology to create a database using linked administrative data. Using clusters of worker flows between firms, movements of clusters firms between tax consolidated groups, and details of firms lodging forms related to takeovers and schemes of arrangement, we find around 1,500 mergers a year. Regressions confirm that the likelihood of being an acquirer rises dramatically with size of the enterprise groups. Acquirers also tend to have registered trademarks. Targets are most likely to be members of enterprise groups or smaller businesses and have lower productivity. This is the first step in a rich field of future research in Australia and will allow researchers to answer questions including: what happens to workers of firms that merge; what subsequent financial and investment performance of merged firms looks like; and whether managerial quality makes a difference (amongst many others). The set of research questions that can be explored will also expand as new datasets are integrated into the data sharing ecosystem.

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Appendix 2 .A Administrative forms used to determine merger

Acquirer	Target	Form name	Form code
Off market takeovers			
✓		Off market bid	6321B
✓		Bidder statement and offer - off market	6181
	✓	Target statement and report - off market	6211
✓		Notice of service of bidder's statement - off market	6011
✓		Notice that takeover offers have been sent - off market	6201
✓		Notice of status of defeating conditions	672
✓		Defeating condition near end of offer period	672B
✓		Defeating condition fulfilled	672A
✓		Notice offers free of defeating condition - off market bid	6261
✓		Notice date set for determining securities holders - off market	670
On market takeovers			
✓		Market bid	6321A
✓		Takeover bidders statement & docs sent to exchange	6291
✓		Target statement and report - on market	6331
✓		Document accompanying bidders statement - on market bid	6301

Table 2 .6: Takeovers forms

Acquirer	Target	Form name	Form code
Compulsory acquisitions			
✓		Notice of compulsory acquisition following takeover bid	6021
✓		Notice of right of buy out to remaining holder of securities following a takeover bid	6022
✓		Notice of right of buy out to holders of convertible securities following a takeover bid	6023
Additional statements			
✓	✓	Supplementary statement re takeover bid	675
✓		Bidder's supplementary statement	675A
	✓	Target's supplementary statement	675B
✓		Replacement bidder statement	675C
✓		Replacement bidder statement marked up	675D
✓	✓	Court order re proportional takeover in constitution	6271
✓		Notice of variation in takeover offer	6321
✓		Notice of disclosure re substantial shareholding in bid period	671

Table 2 .7: Takeovers forms - additional

Chapter 3

Promotion in the Australian Public Service: Improvements for women and stagnation for cultural and linguistic minorities

3 .1 Introduction

We examine promotion and separation in the Australian Public Service (APS) from 2001 to 2020 by gender and for three other Equal Employment Opportunity (EEO) groups - people with a disability, Indigenous Australians and people from non-English speaking backgrounds (NESB). We use the universe of personnel records of the APS and estimate logit models of the probabilities of promotion and separation. The data allow us to identify membership in an EEO group and to control for observable characteristics related to productivity and employment.

Our results help deepen our understanding of the composition of the public service, EEO representation, its evolution over time and the degree to which it reflects the diversity of Australia. Our research is particularly important given that Australia is one of the world's most multi-cultural countries. More than half of Australians are first or second generation immigrants (Australian Bureau of Statistics 2021).

Promotion prospects for women have improved substantially over time at all levels. By 2020, women are as likely as similar men to be promoted at junior levels and more likely than men to be promoted at senior levels. This holds after controlling for a range of skills and experience. Improvements in promotion prospects accelerate after 2012, when gender diversity strategies were implemented by the APS. This provides suggestive evidence that policies like aspirational gender targets, organisational champions and public awareness affected women's promotion prospects.

For people with a disability, promotion prospects are lower than for similar individuals who do not report a disability. There are no improvements over time, except at the lowest level of the APS. This is despite an explicit disability strategy being in place within the APS since 2012.

For Indigenous Australians, promotion prospects are much worse than non-Indigenous people at all levels except the most senior. Again, except at the two most senior levels, promotion prospects do not appear to have improved over time despite explicit ABS strategies to recruit and retain Indigenous staff.

For NESB, promotion prospects have stagnated or become worse over time. The promotion penalty for being in the NESB group is larger at higher ranks of the public service. The penalty is present for Australian-born NESB and those who migrated to Australia at a very young age. This argues against an explanation driven entirely by language barriers or cultural assimilation. We also rule out an explanation for occupational segregation within the public service.

When we look at the probability of separation, we find little difference between men and women. People with a disability and NESB are less likely to separate from the public service. Lower promotion prospects do not appear

to lead to greater exit. This could reflect unobserved characteristics of this group or it could reflect employment barriers outside of the public service for these groups. Indigenous staff at all levels are more likely to separate from the public service.

Care should be exercised in interpreting our results. We observe some, but not all, individual characteristics. We do not observe: performance evaluations; success at current job level; promotion applications or outcomes for those who leave the public service. While we caution against a causal interpretation, the results raise several troubling questions. For Indigenous staff, the low rates of promotion and retention could suggest a problem of feeling unwelcome in the APS that needs to be addressed. For the NESB group, if being from a non-European background is a barrier to advancement even when someone is fluent in English and raised in Australia, there may be a problem of racism and bias in the public service. If nothing else, these findings warrant further attention and investigation by the APS.

Our study, using the entire census of Australian Public Service employees, makes three main contributions to the existing literature. Our paper is unique in studying the impact of immigrating versus being native-born or raised on public sector promotion and separation prospects. Our data allow us to consider promotion at each separate level of the public service. This controls for the possibility of different entry levels granting employees different promotion prospects and allows us to investigate the possible existence of 'glass ceilings.' Our paper provides new evidence for Australia and represents the first comprehensive analysis of promotions and separations for the Australian public service. This complements research from other countries, including the US. Much of the previous research has used small samples rather than a full census, as we do.

The rest of the paper proceeds as follows: we provide additional background in Section 3 .2; Section 3 .3 provides a summary of the literature; Section 3 .4 provides an overview of the Australian Public Service Employment Database (APSED); Section 3 .5 discusses the methodology for modelling promotion and separation, followed by a discussion of results in Section 3 .6. We dig deeper into the results in Section 3 .7 to explore the role of language fluency and cultural assimilation and to examine how promotion prospects have evolved over time. We conclude in Section 3 .8.

3 .2 Background

Australia is a highly successful multicultural country with an orderly immigration system underpinned by its skilled migration intake. The 2021 Census indicates that more than half of Australians are either first or second generation immigrants. The largest group of immigrants were born in the UK, closely followed by those born in Asia. Reflecting this diversity, 15 per cent of staff in the Australian Public Service (APS) are from a non-English speaking background (NESB).

However, NESB staff held only 7 per cent of Senior Executive (SES) positions in 2022 (Australian Public Service Commission 2022).[1] Similar patterns of under-representation are evident for other EEO groups. Women make up around 60 per cent of all APS employees and hold just over half of all SES positions. Indigenous staff make up around 3.5 per cent of the APS, slightly more than their share in the general population, but hold only 1.4 per cent of SES positions.[2] Lastly, staff with a disability make up around 4.7 per cent of the APS and hold 4.2 per cent of all SES positions. Similar to the APS, women and minorities are underrepresented at the higher echelons of the US Federal civil service (Choi 2011; Marvel 2021). 2023 figures show that while the Canadian public service has been broadly representative of women, Indigenous and staff with a disability at its highest (Executive) classification, visible ethnic minorities are substantially underrepresented.[3] 2024 UK data show that the UK public service has significant under-representation for all EEO cohorts at the Senior Civil Service level.[4]

[1]The Senior Executive Service (SES) are the leadership cohort in the Australian public service and are similar to the US Federal Government's SES, and the UK's Senior Civil Service. Executive Level 1 and Executive Level 2 ranks often hold managerial responsibilities, while APS-level staff may hold a wide range of analyst, operational, support and other positions.

[2]According to the 2021 Census, Aboriginal and Torres Strait Islander People comprise 3.2 per cent of the Australian population. We use the term Indigenous as a generic term covering both groups.

[3]See `https://hrdatahub-centrededonneesrh.tbs-sct.gc.ca/?GoCTemplateCulture=en-CA#ReportSectionTopDiv`.

[4]16.6% of staff belong to an ethnic minority or are mixed, 55% of staff are women, 16.9% have a disability. For the Senior Civil Service the corresponding numbers are 10.6%, 48.2% and 10.8%. See `https://www.gov.uk/government/statistics/civil-service-statistics-2024`.

Throughout this paper, NESB refers to people who are:

- born outside Australia and whose first language is not English; or
- born in Australia, whose first language is not English and either mother's or father's first language is not English; or
- born in Australia or overseas where both parents' first language is not English.

This definition of NESB is used by the APS for their internal reporting. We apply this definition in our analysis. The data do not include information on race or ethnicity. We use a combination of this NESB definition and country/region of birth to approximate ethnicity.

Policy landscape

Australia has a long-standing prohibition against racial discrimination. The *Racial Discrimination Act 1975* made it unlawful to discriminate on the basis of race, colour, descent or national or ethnic origin. It afforded persons of all races and ethnic origins equality before the law in matters such as employment or seeking promotions. Similarly, the *Disability Discrimination Act 1992* made it unlawful for employers to discriminate against a person on the grounds of disability. Amendments to this Act were introduced in 2005 requiring employers to make reasonable adjustments to eliminate discrimination. The Australian Human Rights Commission is responsible for enforcing national and state-level equal opportunity and anti-discrimination laws (Australian Human Rights Commission 2023).

The *Sex Discrimination Act 1984* prohibits discrimination against persons on the ground of sex, marital status or pregnancy at work, and discrimination involving sexual harassment in the workplace. This was strengthened by the *Equal Opportunity for Women in the Workplace Act 1999*, designed to promote the principle that employment for women should be on the basis of merit. It sought to promote, amongst employers, the elimination of discrimination against women and the provision of equal opportunity for women in relation to employment matters. Rather than merely prohibit sex discrimination, this Act required employers to actively develop equal opportunity for women programs under the direction of a senior officer in the organisation. It required reporting by higher education institutions and employers with more than 100 employees (mostly excluding the government sector). It established the Equal Opportunity for Women in the Workplace Agency, whose function was to assist and advise employers, conduct research and issue guidelines under the Act. The *Equal Opportunity for Women in the Workplace Act 1999* was replaced by the *Workplace Gender Equality Act 2012* (WGEA Act), which extended coverage to include men. The new Act covered all workplaces irrespective of size but smaller organisations are exempt from the reporting requirements.

Hiring and promotion in the APS is governed by legislation. The *Public Service Act 1999* introduced the requirement that all employment decisions be based on merit. It required the APS to provide a workplace free from discrimination that recognises and utilises the diversity of the Australian community. It required agency heads to establish workplace diversity programs. Following legislative amendments in 2013, the APS Commissioner issued the *Australian Public Service Commissioner's Directions 2013*, which set clear expectations that agency heads include measures directed at eliminating employment-related disadvantage on the basis of gender, race or ethnicity, disability or being a member of a group that is identified as having an employment-related disadvantage. In particular, agency heads were required to create workplace structures, systems and procedures to assist employees in balancing work, family and other caring responsibilities. They were required to develop strategies to attract, recruit and retain employees that reflect the diversity of the Australian community.

Affirmative action measures accompanied these 2013 legislative amendments. They allowed agency heads to identify a vacancy as open only to people with an intellectual disability. They provided for engagement of persons with disability who have been assessed as being unable to participate in a competitive selection process. These affirmative action measures were strengthened by the *Australian Public Service Commissioner's Directions 2016* which included additional measures to support the engagement of persons with disability. Indigenous affirmative action measures were expanded to include selection of persons for short-term, non-ongoing engagements as well as broad affirmative action targets.

Momentum for gender equality in the APS accelerated alongside the 2012 passage of the WGEA Act. The APS committed itself to "lead the way in improving gender equality in the workforce" (Australian Public Service Commission 2016b). This focus culminated in policies setting gender equality targets on government statutory boards and at senior levels of the APS. Agency heads became accountable for meeting these targets through their performance agreements (Australian Public Service Commission 2016b).

The Commonwealth Aboriginal and Torres Strait Islander Employment Strategy 2015-2018 set a goal of increasing the representation of Indigenous employees across the Commonwealth public sector to three percent by 2018 (Inside Policy 2019). In 2019, the APSC released a new Indigenous employment strategy (Australian Public Service Commission 2019). In November, 2023, the Australian government announced a new strategy to double the number of Indigenous SES to 100 (Prime Minister and Cabinet 2023).

A disability strategy was first published in 2012 and strengthened in 2016 (Australian Public Service Commission 2016a). These two strategies aimed to expand the range of employment opportunities for people with a disability, invest in their capabilities and increase representation at senior roles to foster an inclusive culture. In contrast to the gender and disability policies, the APS has never issued an employment strategy in relation to NESB staff to the authors' knowledge.[5]

3 .3 Related Literature

A common way to approach questions about the relative economic position of women and minority groups is to calculate wage and other 'gaps' and decompose the contribution of a range of factors associated with productivity such as education and experience (Blinder 1973; Oaxaca 1973). The literature on the factors influencing promotions is more sparse, perhaps due to the challenges of comparing position titles across organisations, difficulties in disentangling wage movements from promotions and lack of access to data.

To study public service promotions, retention and performance, many scholars have used the Federal US government's personnel management database (the Central Personnel Data File, or CPDF) which contain records of Federal civilian employees (Choi and Rainey 2010; Choi 2011). Similar to the APS, the US civil service classifies positions across agencies into different grades, with grade increases reflecting higher salary, status, authority and responsibility. Thus, movements up grades can be considered as genuine promotions, and can be clearly distinguished from salary increases, which are also a function of seniority within a grade.

Studies of the US Federal Civil Service

Analysis using personnel records, mostly from the CPDF database, of Federal US employees has found mixed results on the impact of gender and being black on promotion probabilities (Lewis 1986; Rich 1997; Marvel 2021) while significantly lower promotion prospects have been found for Indigenous men and women, Asian men and women and staff with disabilities (Lewis and Allee 1992).

These studies have modelled promotions as either the probability of being promoted in a given year, controlling for grade levels (Lewis 1986; Lewis and Allee 1992; Marvel 2021) or the total number of promotions over a period of time (Lewis 1986). In an important early study, Lewis (1986) analyzes gender differences in promotions amongst white-collar, full-time, white workers in the US Federal civil service. The study does not find strong evidence of gender discrimination, with statistically significant results (in favour of male promotion prospects) found in only two of the 18 years analyzed. In contrast, differences in promotion probabilities between men and women have been found when analyzing blue collar jobs (Rich 1997). She finds that the higher number of promotions of women is partly due to their starting in lower-paid clerical occupations compared to professional and administrative jobs for men. This is supported by remuneration outcomes: women start on lower salaries and gain less money from promotions than men despite the fact that they are more likely to have a higher number of promotions in total.

[5] A strategy in relation to culturally and linguistically diverse staff is under development at time of writing; see Australian Public Service Commission (2023).

Using detailed, person-level data over the years 1979 to 2013, Marvel (2021) examines the influence of occupation, race and sex on whether staff are more likely to be promoted to the Senior Executive Service (SES) of US federal agencies. He shows that the dominant occupation of each agency (such as program management or STEM occupations) is influential in promotion prospects, but race and sex are not after controlling for 'quality' as measured by speed of past promotions, pay increases and bonuses. In contrast to our study, Marvel's data only includes employees who are eligible to be promoted to SES.

The issue of starting grades affecting promotion prospects is also relevant when analysing race, and other 'diversity' outcomes. Rich (1997) finds that not only do white staff have a higher probability of promotion than black staff, they start on higher salaries and gain more money from their promotions.

Intersectionality may also matter: in the presence of occupational segregation, it is possible that white women compete with ethnic minority women, which could artificially increase white women's promotion chances if minority women face harsher discrimination than minority men do. Lewis (1986) finds some evidence for better promotion prospects for white women compared to non-white women and the opposite for men.

It appears that the US government no longer makes unit record data available through the CPDF. It has been replaced by summary statistics from the federal administrative civilian personnel data released in a product called 'Fedscope'. Recent literature has thus been qualitative and uses the experience of senior executives, sometimes using very small samples. Other research has used employee surveys and focused on topics such as employee wellbeing rather than promotion or wage equality.

Wyatt and Silvester (2015) reviewed the experience of 12 women who had reached senior executive roles in the US Federal bureaucracy. Lam (2020) surveys 53 current employees and 102 recent hires in the US Department of Commerce and found that Hispanics have a less favourable view of the federal government compared to other groups. Choi and Rainey (2014) use the 2006 Federal Human Capital Survey and find that in an agency where members perceive higher levels of organizational fairness, and where employees perceive that diversity is more effectively managed, employees report higher satisfaction with their jobs.

Public service diversity, incentives and performance

Our research has relevance for the growing literature on the impact of diversity and inclusion policies on workplace performance. Rafaqat et al. (2022) reviews the literature of the last two decades and finds that workforce diversity is significantly related to organizational performance.

A large literature documents the effect of financial and promotion incentives on public sector performance. Overall, empirical evidence across all sectors – private, public and non-profit – points to the positive average effect of monetary incentives on employee productivity - see Nistotskaya (2018) for a review of the evidence. However, when promotions are not meritocratic (for example when career advancement is achieved through social interactions rather than performance, Cullen and Perez-Truglia (2019)), increasing the pay gradient reduces worker productivity through negative morale effects (Deserranno et al. 2021). Similarly, Karachiwalla and Park (2016) find that teachers reduce effort if repeatedly passed over for promotion.

Other factors: Non-English Speaking Background, Immigrants, Language Fluency and Race

Breunig et al. (2013) find wage gaps for immigrant NESB men and women in Australia and, while wage convergence does occur over time, it is slowest for NESB immigrants. Booth et al. (2012) conducted a field experiment in Australia using work resumés with Anglo-Celtic and minority ethnic[6] names included at the top of the resumé. Applicants for entry-level roles with minority ethnic names need to apply for more jobs in order to receive the same number of interviews as their counterparts with Anglo-Celtic names.

Adamovic and Leibbrandt (2023), based upon a field experiment in Australia, conclude that discrimination against ethnic minorities worsens as they climb the career ladder into leadership roles. They submitted 12,000 job applications

[6]Defined as those with Indigenous, Italian, Chinese or Middle Eastern names.

to over 4,000 job advertisements, to investigate hiring discrimination against six ethnic groups for leadership positions. Applicants with names derived from ethnic minorities received 57.4 per cent fewer positive responses than applicants with English names for leadership positions despite identical resumes. Non-leadership positions drew 45.3 per cent fewer positive responses. Ethnic discrimination for leadership positions was more pronounced when the advertised job required customer contact.

A large literature from the private sector in the US and Canada find women and ethnic minorities are disadvantaged in promotion prospects and in retaining their jobs compared to white males. Minority executives experience lower promotion, higher demotion and higher exit rates (Guest 2016; Wilson and Maume 2013). From blue collar jobs, African Americans (Latinos) are 25 (18) per cent less likely to attain management positions compared to Whites (Wilson and Maume 2013). For women and racial minorities, promotion is less likely than for men and the disadvantage is most severe at the lower rungs of the organizational hierarchy (Yap and Konrad 2009), similar to what we find for the APS.

Fitzsimmons et al. (2020) study labor market outcomes of first and second generation immigrants in Canada, controlling for skin colour, language and gender. Without controlling for these factors, the pay and promotion prospects of immigrants were lower than the native population. However, once these factors are added, they find white male immigrants who speak English fare better than the native population.

In a qualitative study, Lashley (2013) emphasizes concerns about the culture of the UK civil service by examining how 20 black and minority ethnic and 20 white senior managers from a UK government department made sense of significant career incidents in their leadership journeys. Cooper and Turgeon (2024) use data from the Canadian Public Service Employee Survey to test whether public servants' ability to use their official language of choice at work is related to their turnover intentions. They find that ability to use the language of choice at work impacts internal and external turnover intentions.

One possible explanation for the results with respect to ethnic minorities or migrants is that employers infer lack of language fluency and cultural understanding from ethnicity or family name when assessing job applicants. These assumptions then lead to poorer labor market outcomes in service sectors such as the public service. Since service sector occupations rely on people-to-people interactions, another possibility is that minorities may be disadvantaged when interacting with the majority due to (real or perceived) racial, ethnic, cultural and linguistic differences. For example, Borghans et al. (2014) find the increasing demand for 'people skills' between the late 1970s and 1990s in the United States explains movements in the gender and black-white wage gaps.

Language fluency may assist in acquiring information about optimal job search strategies and convincing employers of a candidate's qualifications. Language fluency is a prerequisite for many unskilled jobs. Using data from France, Germany and the UK, Dustmann and Fabbri (2003) find language fluency increases employment probabilities, but the effect is stronger for males than females. These findings on the importance of fluency are supported by Borjas (2015), who examines the evolution of immigrant earnings in the United States from 1970 to 2010. He finds that more recent cohorts may have experienced less economic assimilation partly due to lower investment in English language proficiency.

In our analysis, we examine the issues highlighted in this literature. We consider promotion outcomes of all NESB. We then analyze the NESB group separately by those who are born in Australia or who arrived before the age of 6 in order to gain some understanding of the impact of language fluency and cultural assimilation. We separately analyze Asian-born NESB to learn more about the effect of race.

3 .4 The APSED data

We use a version of the APS Employment Database (APSED) covering 2001-2020 that has had identifying information, including agency/department, removed.[7] APSED is a high-quality personnel database that tracks the employment, promotion, separation and other details of every employee in the Australian Public Service (APS). The APSC creates

[7]APSED is not publicly available but the authors are happy to assist other researchers in obtaining the data from the Australian Public Service Commission. Appendix C provides details on our data construction.

a 'snapshot' report twice-yearly on the employee characteristics of the APS (Australian Public Service Commission 2021a). We utilise the December snapshots and combine them with another APSC file that tracks movements within the APS to create panel data indexed by a unique identifier for each employee. In December 2020, there were 145,902 ongoing staff of whom 2,834 were in the senior executive service (SES).

By combining the snapshot and movement files, we are able to track the career paths of APS employees through time and across agencies and observe when they separate from (i.e. leave) the public service. The details of the process of merging these two files to produce our analysis data are described in Appendix C. Particular variables of interest in the APSED database are summarised below.

Employment and Promotion: Public servants are categorised into APS (levels 1-6), EL1, EL2 and SES ranks.[8] APS officers usually hold analyst positions while EL1 and EL2 ranks hold mid-management and management positions. SES are the strategic leadership cohort, similar to the SES in the US Federal Public Service and the Senior Civil Service in the UK.

EEO Groups: All EEO characteristics are self-identified or constructed using information supplied by employees. Demographic data are gathered by the APS when individuals begin working in the service. While individuals can update their information at any time, there is no obligation for people to update their status regularly. EEO characteristics are most likely to change when an individual changes agency, at which point demographic data are often, but not always, updated.

Thus, the EEO status of individuals can change. However, there are very few changes in our data. Less than 1.3 per cent of our sample change NESB status, only 1.2 per cent change disability status and less than one per cent change Indigenous status. We code as Indigenous, NESB or having a disability anyone who reports one of these characteristics at any point during their service. Our rationale for doing this is that the willingness of people to report information on their background or on disability may change over time and that people may become more or less reticent about reporting these characteristics. Also, the impact of disability may be present even before it is officially 'reported.' We can also rule out people changing status to take advantage of the various affirmative action programs described in Section 3 .2.

The Indigenous variable is based upon a question asking people if they are "of Aboriginal or Torres Strait Islander origin". The NESB variable is constructed by the Australian Public Service using employee-provided data on country of birth (COB), year of arrival, first language spoken and parents' first language. Specifically, the NESB variable is derived as any employee with the following characteristics:

- COB not Australia and first language is not English; or
- COB Australia, first language not English and either mother's or father's first language not English; or
- COB Australia or overseas, first language is "English" or "English and another language" and both parents' first language is not English.

For some analysis, we combine those who are born in Australia with those who were born overseas and arrive in Australia before the age of 6 and compare them to those born overseas who arrive at age 6 or later. We do this to capture differences in schooling, English language skills and cultural attributes acquired in Australia as opposed to overseas.

For disability, Indigenous and NESB, we treat missing values as being equal to zero. There is no compulsion to answer these EEO questions and the APS does not follow up with individuals who leave these questions unanswered. Our interpretation is that people who don't answer these questions most likely do so because they are not relevant for their situation. We check this by dropping the missing values from our analysis and our results do not change in any substantive way–see Appendix D.

Skills: Skills indicators are derived from the data directly or provided on commencement of employment, often as a pre-condition of engagement. These include being an APS graduate or trainee; holding a bachelor degree or above;

[8]The Senior Executive Service in the APS is divided into three tiers: SES Band 1, SES Band 2 and SES Band 3. In this analysis we only consider promotions from EL2 to SES Band 1. For SES Band 2 and Band 3 classifications, cell counts for promotions of staff who are NESB or who have a disability become very small or even zero in some years.

central agency experience[9]; and a qualification in the field of economics, finance or accounting.

Other Characteristics (Controls): An employee's part-time status[10]; whether an employee is on maternity leave; experience within the public service (i.e., time at level); and age are also included in APSED. For age and experience, we allow quadratic effects. Year fixed effects are also added to control for public sector expansions and promotion freezes. We create a variable which captures the fraction of time which an individual is part-time over their entire career. This variable takes value one if a person has been part-time in all years of their career and zero if the person has never been part time. For someone who has been part-time in three of the five years she is observed in the data, this variable would take value 0.6.

APSED Summary Statistics

Table 3 .1 shows summary statistics for key variables of interest at all levels of seniority used in our analysis pooled over the period 2001 to 2020. It shows that the proportion of those promoted falls from 15.4 per cent (APS5) to 2.1 per cent (EL2) as we move up levels whereas the proportion of those who separate increases from 3.2 per cent (APS4) to 4.6 per cent (EL2).

	APS4	APS5	APS6	El1	EL2	SES
Promotion	0.097	0.154	0.085	0.047	0.021	n/a
Separation	0.032	0.035	0.039	0.041	0.046	n/a
Female	0.679	0.579	0.544	0.485	0.404	0.392
Disability	0.069	0.054	0.054	0.052	0.05	0.056
Indigenous	0.039	0.029	0.017	0.014	0.01	0.01
Non-English Speaking Background	0.148	0.146	0.153	0.138	0.102	0.065
Asian-born NESB	0.046	0.050	0.056	0.050	0.028	0.012
European-born NESB	0.018	0.019	0.021	0.020	0.017	0.011
Accounting/Economics/Finance degree	0.04	0.054	0.067	0.094	0.119	0.175
Bachelors or Above	0.202	0.306	0.443	0.544	0.642	0.727
Graduate Program	0.079	0.142	0.135	0.165	0.183	0.263
Central Agency Experience	0.029	0.053	0.059	0.096	0.124	0.255
Part-Time	0.186	0.104	0.121	0.109	0.071	0.026
Maternity leave	0.027	0.020	0.022	0.020	0.012	0.004
Arrived age 5 or younger	0.130	0.127	0.139	0.135	0.119	0.091
Arrived age 5 or younger (NESB)	0.072	0.070	0.078	0.070	0.046	0.020
Arrived age 5 or younger(Asian-born NESB)	0.040	0.041	0.048	0.043	0.024	0.009
Born in Australia	0.667	0.658	0.653	0.664	0.654	0.709
Asian-born ESB	0.022	0.023	0.025	0.022	0.018	0.014
Observations	665,483	467,175	662,308	505,511	232,983	47,427

Values in cells are proportions of individuals in the data for whom the variable is equal to one.
Standard deviations can be calculated as $p(1-p)$.
Note: SES is the top level so there is no promotion. Most SES are on contracts and rather than separating, they leave when they come to the end of their contract.

Table 3 .1: Summary Statistics of Main Variables of Interest

The proportion of staff with characteristics related to skills increases at each level. For example, at the APS4 level 20.2 per cent have a bachelors degree or above while 64.2 (73) per cent of those at EL2 (SES) level have a bachelors or above. In contrast, the proportion of those from an EEO group (non-English speaking background, disability, female) is lowest at the highest levels. The proportion of those working part-time also falls as people move up levels.

Figure 3 .1 shows the relative promotion prospects at all levels for the four equal opportunity employment groups. We see lower promotion prospects at most levels for the four groups. We explore these differences further, and

[9]Central agencies are defined as Prime Minister and Cabinet (PM&C), Treasury and Finance. The APS provided us an indicator variable for individuals being in one of these three agencies.

[10]Breunig and Rospabe (2013) document the importance of part-time status in explaining wage gaps between male and female employees in the public sector in France.

control for observable, productivity-related characteristics in what follows.

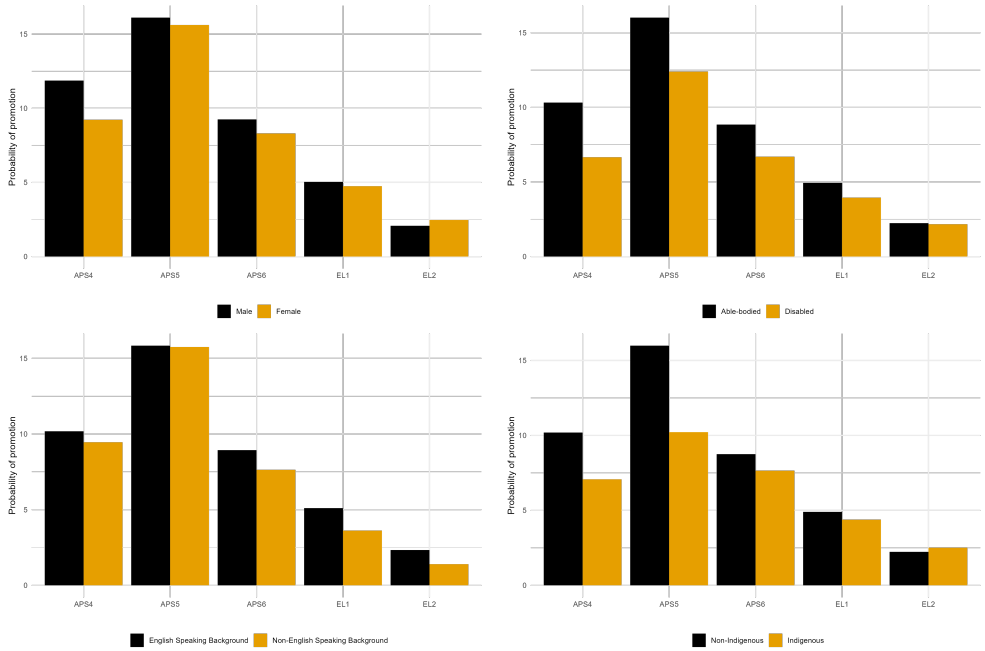

Figure 3 .1: Promotion probabilities of equal opportunity employment groups

Appendix A presents descriptive statistics for each level of seniority for three points in time: 2002, 2010 and 2020. The proportion of female individuals has increased over time at all levels of the APS. The proportion of people who report a disability has decreased over time at all levels in the APS. The proportion of NESB in the public service has increased over this time period at all levels with the exception of the SES level where the proportion of NESB individuals has remained just over 6 per cent. We look at the time trends in the data with respect to relative promotion probabilities in more depth in section 3 .7.

Australian Public Service Gazette data

To check that these patterns hold in other sources, we examined publicly available data from the APS Gazette.[11] Using OnoMap[12] (following Booth et al. (2012)) we infer the ethnicity of last names of all staff promoted in the APS from 2002-03 to 2021-22. While around 12 per cent of promotions at junior and analyst ranks are of staff with non-European names,[13] this falls to 10 per cent for mid-management/management promotions (EL1 or EL2) and 4 per cent for SES promotions. Over the past two decades, around 96 per cent of promotions to SES were awarded to staff carrying Anglo, Celtic or European names.

What might be driving these patterns in APS employment? Could there be characteristics related to productivity (such as years and type of experience, education and English fluency) that contribute to career success for different groups? Or could different rates of attrition play a role? To disentangle these effects, we explore the impact of these factors on promotion and separation prospects for different EEO groups and eliminate a number of possible explanations.

3 .5 Modelling career movement

In each period APS staff at each level either leave, stay at level or get promoted. To analyse the determinants of these alternatives, we estimate logit models of promotion and separation to analyse the influence of an individual's

[11]The APS Gazette (APS Jobs 2023) publishes names of individuals engaged by, or promoted in, the APS. A small number of names are excluded for national security reasons. The authors are happy to share these data upon request.

[12]The OnoMap family of software tools is widely used in research for the classification of names; Onomap (2022).

[13]'Non-European' means those names that are not Anglo, Celtic or European including those that can not be classified.

skills and characteristics on these outcomes while controlling for a range of factors.

Let X_{it} stand for the characteristics of individual i at time t. $Y_{i,t+1}$ is the binary outcome for individual i at time $t+1$: either promotion or separation. Separation includes voluntary resignation, voluntary and involuntary redundancy and other terminations, but excludes retirement, death, and invalidity.

The conditional probability of $Y_{i,t+1}$ equaling one is modeled as:

$$Prob\left(Y_{i,t+1}=1|X_{it}\right)=F\left(X_{it}\right) \tag{3 .1}$$

where F is the logistic function. X_{it} includes a constant, characteristics which vary over individuals and time and year fixed effects, which do not vary across individuals.

Individual characteristics include whether the staff member has a Bachelor's degree or above, has central agency experience, was part of an APS graduate intake or has a degree in economics, accounting or finance. We also control for experience at level and its square, age and its square, part-time status, maternity leave status and year (to account for public service recruitment and promotion freezes). For part-time status, we control for an individual's current part-time status and we include an indicator if an individual has been part-time throughout their entire career. We also include a rolling variable which captures the percentage of an individual's career inside the APS which has been part-time; see Section 3 .4 above.

Relevant work experience outside the APS is not available in APSED. Including age will, to some degree, pick up work experience outside the APS. The vast majority of public servants are located in the federal capital, Canberra. We have location data available but these data correspond to the position and not to the physical location of the individual. For example, a person could live and work in Sydney but hold a position that is Canberra-based. Including location data does not change our results and we omit it from all of our models.[14]

In both models (for promotion and separation), $Y_{it+1}=0$ for those who remain with the APS and remain at level. For the models of promotion, we are thus estimating over the subset of those who are promoted and those who remain with the APS. We exclude those who separate. For the models of separation, we estimate over the subset of those who separate and those who remain at level with the APS. We exclude those who are promoted. We estimated multinomial logit models with all three outcomes and the results are similar.[15] The assumption of independence of irrelevant alternatives which underpins the multinomial logit model is inappropriate in this situation and we thus prefer the results from the two distinct logit models. We pool data across multiple years in estimation so we cluster the standard errors at the level of the individual. We focus on odds ratios in our discussion of the results in the next section. Details of coefficient estimates from all models that we estimate are provided in Appendix B.

3 .6 Results

We begin by estimating baseline models using equation (3 .1) for promotion and separation for all individuals pooled across all years of our data. For coefficient estimates, see Appendix Tables 3 .8 and 3 .17. We summarise the results, first for promotion and then for separation. We focus on the marginal effects from the model - that is, what is the relative probability of promotion for groups with different attributes conditional on all other characteristics. We present these marginal effects in graphical form.

Promotion: Equal Employment Opportunity (EEO)

Figure 3 .2 compares the probability of promotion of the first group to the second group in each panel of the figure. These estimates are based upon logistic regressions using data pooled across all twenty years of our data and control for all other observable skills and attributes. The first panel of Figure 3 .2 compares promotion probabilities for men and women conditional on all other observable characteristics. Men have higher promotion probabilities than women at all levels from APS4 to EL1. However, and somewhat strikingly, women have higher promotion probabilities than men when going from EL2 to the top level of SES.

[14] Results including location are available from the authors upon request.
[15] We do not report these results. They are available from the authors upon request.

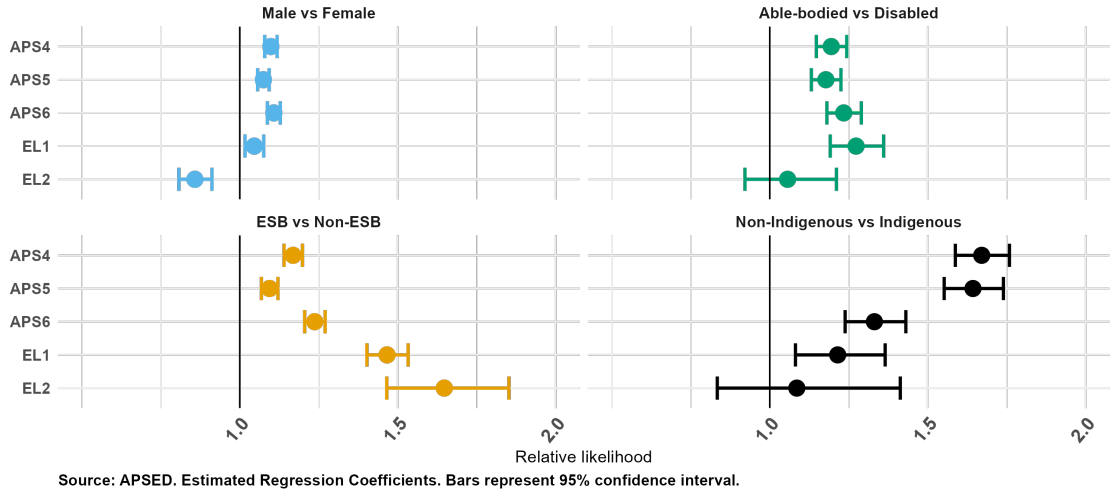

Figure 3 .2: Promotion and EEO Characteristics

The second panel compares those with and without disability. At all levels from APS4 through EL1, people who do not report a disability have higher probabilities of promotion. These are statistically different than zero at the five per cent level as the 95 per cent confidence intervals exclude the 'Just as likely' line. At the top level, promotion from EL2 to SES, there is no statistically significant difference in promotion probabilities between those who report or do not report a disability. This is partly due to the wide confidence interval.

The gap in promotion probabilities between men and women at the APS4 to EL1 levels is about half as large as the gap between people with and without disability. This is reflected in the estimates from Table 3 .8 where the coefficient on 'disability' is about twice that of 'female' at these levels.

The most striking results in Figure 3 .2 are from the bottom two panels. On the left-hand side, we compare those from an English-speaking background (ESB) and those from a non-English speaking background (NESB). The NESB group have lower probabilities of promotion at every level and the difference is statistically significant. Unlike for women and those with disabilities, the NESB promotion prospects decrease at higher levels. For promotion for EL2 to SES, those in the ESB group are about 70 per cent more likely to be promoted than those from the NESB group, conditional on all other observable characteristics.

On the right-hand side, we observe that promotion prospects for Indigenous Australians are very poor. They are about 70 per cent less likely to be promoted from APS4 or APS5 level than similar non-Indigenous people. The numbers improve slightly at higher levels, becoming statistically insignificant for promotion from EL2 to SES due to the small sample of Indigenous people at this level.

Separation: Equal Employment Opportunity (EEO)

Could these promotion outcomes be driven by differing rates of attrition? Figure 3 .3 shows that disability is associated with a lower probability of separation, except at the EL2 level. Being from a non-English speaking background is also associated with being less likely to separate from the APS at all levels. Gender does not seem to have much relationship with separation from the APS. Women are more likely to separate at higher levels which matches their higher promotion prospects at those higher levels.

Indigenous Australians are more likely to separate than similar non-Indigenous individuals. This could be due both to the lack of promotion prospects and to Indigenous people feeling unwelcome or tokenised in the public service. For qualitative evidence and instances where employees perceive these barriers, see Bargallie (2020) and Faulkner and Lahn (2020).

The disability and NESB results are perhaps surprising. If these characteristics are associated with a lower likelihood of promotion, then we might expect these same characteristics to be associated with a higher likelihood of separation

as workers may seek employment outside the APS. However, we do not observe this. In fact, we observe the opposite. One possibility is that these individuals prefer to work in the APS for reasons that we do not observe. Another is that promotion prospects for this group outside the APS may not be better than within the APS. For NESB staff, the low proportions of non-Europeans in senior leadership positions in the private sector (see Diversity Council of Australia (2018) and section 3 .3 above) may mean that they see little benefit in switching careers, especially where such switching may be costly.

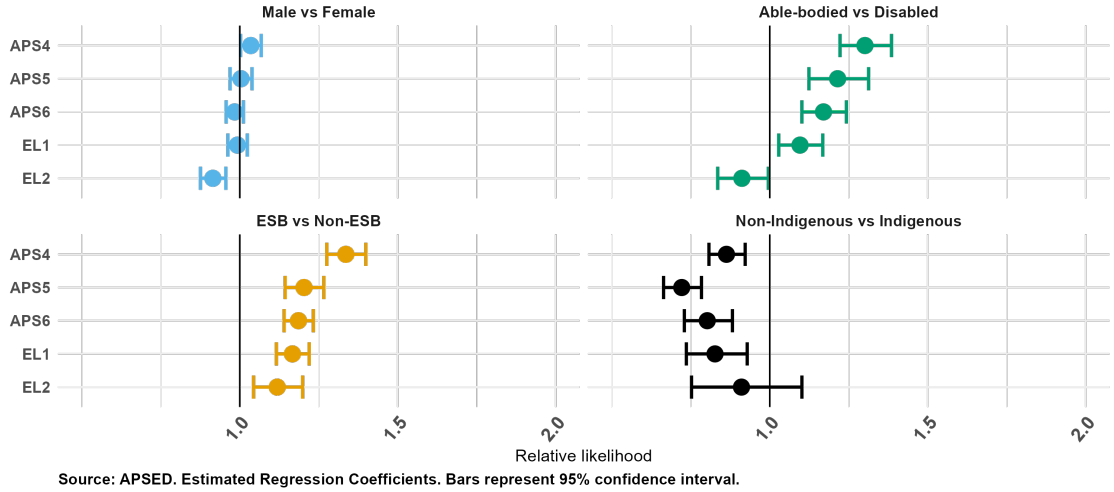

Figure 3 .3: Separation and EEO Characteristics

Promotion: Skills

Figure 3 .4 shows how skills are related to the probability of promotion from each level. Having a bachelor degree or above is important at junior levels. Having qualifications in the fields of accounting, economics or finance seem to matter little for promotion prospects. This is a commonly held belief by Australian public servants and it is interesting to see that there seems to be little evidence of this in the data once we control for other characteristics. Graduate program participation has statistically significant results at most levels but they are inconsistent, with a negative effect for promotion from APS5 to APS6 level and a positive effect for promotion from APS4, APS6 or EL2 levels. It is not clear what we should infer from this pattern.

Experience with a central agency is positive and highly statistically significant at all levels; for example, staff with experience in a central agency are around twice as likely to be promoted from EL2 to SES relative to those with no central agency experience. This may reflect skills that are acquired at a central agency or may be picking up selection effects. Unobserved characteristics about an individual that make them more likely to get promoted may be correlated with being more likely to work or have worked at a central agency.

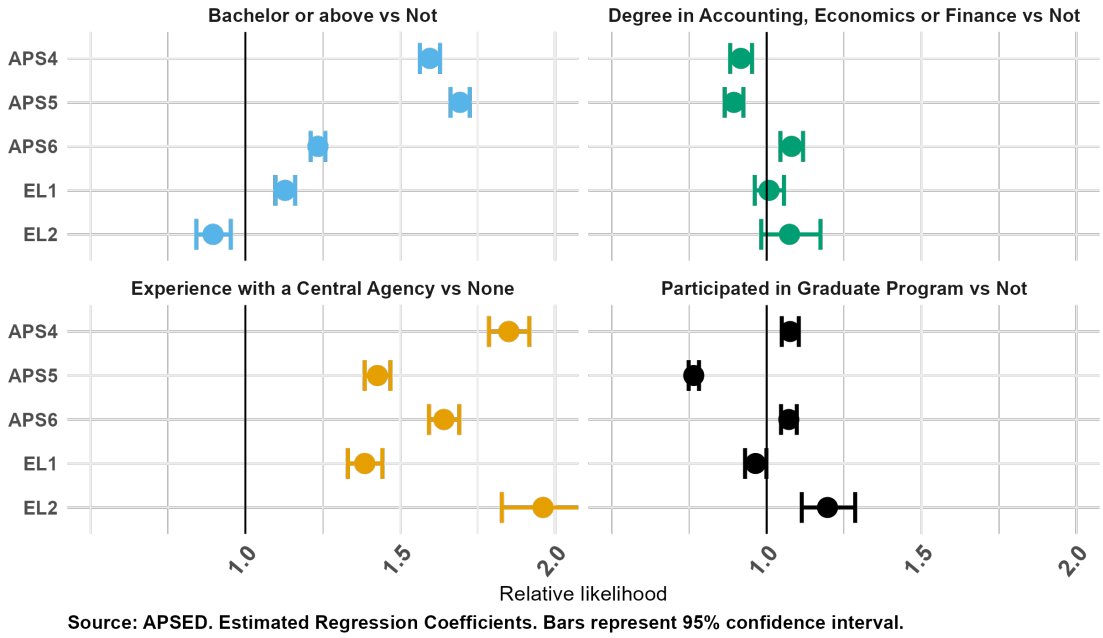

Figure 3 .4: Likelihood of promotion and Skills

Separation: Skills

Figure 3 .5 shows how skills influence the probability of separation from APS4 to EL2. It shows that having a bachelor degree or above has little influence on whether staff continue to be employed with the APS at the APS4 and APS5 levels. However, once people become more senior, having a bachelor degree or above lowers the probability of separation and this effect is larger at higher levels. In contrast, those with degrees in accounting, economics or finance are less likely to leave the APS when they are below EL1 level. However, EL2 individuals with a degree in one of these fields are more likely than similar colleagues to depart the APS.

Experience with a central agency makes leaving the APS more likely at levels below EL1. The coefficient for departures from APS5 is only significant at the 10 per cent level.

Entering the public service via the graduate program is associated with a lower probability of separation at higher levels–specifically EL1 and EL2. It is associated with a higher level of departure for those at APS4 level. Those in the graduate program are viewed as being selected for future leadership potential and some of them may use this reputational signal early in their career to leave the service quickly.

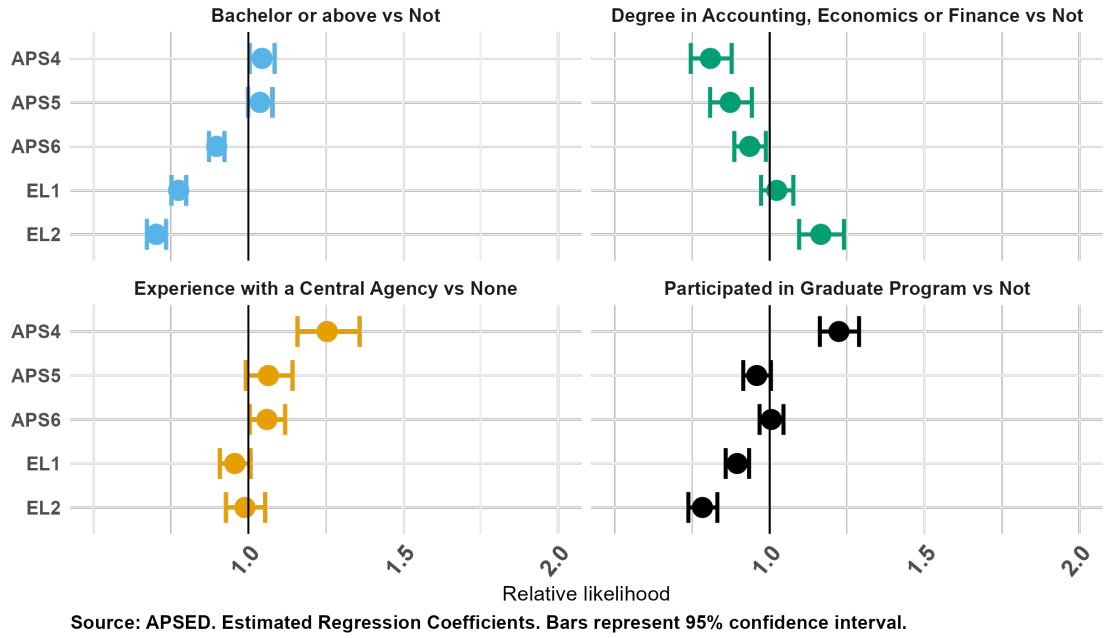

Figure 3 .5: Separation and Skills

3 .7 Digging deeper

In this section we explore these results in more depth. First, we examine the results for those from non-English speaking backgrounds (NESB). Their lower probabilities of promotion relative to similar, ESB employees raise several questions. First, is this driven by language ability or cultural fluency? Second, could this be driven by race? Recall that we do not have data on ethnicity or race, but we do know country of birth and we can use this as a rough proxy for race.

A third explanation is that these results are affected by occupational segregation within the public service. There is a stereotype that NESB individuals are often in more 'technical' jobs which have lower promotion prospects than more 'general' and managerial jobs. Women may also be concentrated in administrative positions with little prospect for promotion. Considering promotion at each level, as we do, controls for some of this occupational segregation but we can also use data on job families to examine these hypotheses. Job family data are only available for the most recent years.

The literature from the US, see Lewis (1986) and Lewis and Allee (1992), suggests that the effect of disability or NESB might differ for men and women. We explore that hypothesis. Finally, given the changing policy landscape during our analysis period, as described in section 3 .2 above, do we see changes in the relative promotion probabilities of those from EEO groups over time?

Language and cultural fluency

The relative promotion probabilities for staff from non-English speaking backgrounds (NESB) decrease as we move from lower to higher ranks. To what degree is this related to unobserved language ability or cultural fluency? In other words, are the differences in promotion probabilities that we observe driven by cultural or language barriers that inhibit promotion? This would be possible because a common promotion selection criterion is 'clear verbal and written communication skills'.[16] We also explore whether the act of immigrating to Australia has an effect on promotion prospects, separate from language fluency factors.

[16]The Integrated Leadership System contains criteria for APS staff at all levels and includes "Communicates with influence" as one of five core capability clusters (Australian Public Service Commission 2021b).

In order to answer these questions we split NESB into those who were born in Australia or who migrated before the age of six, and those who migrated at six or older.[17] We also compare NESB and ESB migrants to see if we can separate language effects from cultural assimilation.

Figures 3 .6 and 3 .7 present promotion and separation results from four comparisons. Coefficient estimates from the promotion (P) and separation (S) models are in the Appendix Tables indicated in square brackets:

1. *Australian born or moved to Australia before the age of six:* NESB compared to ESB [P: Table 3 .9; S: Table 3 .18];
2. *Migrants who arrived in Australia after the age of five:* NESB compared to ESB [P: Table 3 .10; S: Table 3 .19];
3. *All ESBs:* ESB who migrated to Australia after the age of five compared to ESBs who were born in Australia or migrated before the age of six [P: Table 3 .11; S: Table 3 .20];
4. *All NESBs:* NESB who migrated to Australia after the age of five compared to NESBs who were born in Australia or migrated before the age of six [P: Table 3 .12; S: Table 3 .21].

The top left panel of Figure 3 .6 shows that among APS staff born in Australia or who arrived prior to the age of six, those with a non-English speaking background are consistently still less likely to be promoted, and the relative probability of promotion falls as we ascend levels. This is despite these staff of non-English speaking background having been educated in Australia and therefore likely to be as fluent in English as staff of English-speaking background. The difference between the relative promotion gaps that we saw in Figure 3 .2 are similar in nature to those in Figure 3 .6. The relative promotion penalties at APS4, APS5 and APS6 levels are nearly the same as when we do not condition on being born in Australia or arriving at a young age. For the EL1 level, the gap is reduced by about 25 per cent and for the EL2 level, the gap is reduced by about 40 per cent.

This is a striking result: the lower promotion probabilities faced by Australian-born or young-arrival NESB staff is almost the same as later-arriving NESB staff until EL levels. This can be seen by looking at the bottom right panel of Figure 3 .6. This is evidence against a simple language or cultural fluency explanation for the poor promotion prospects of NESB Australian Public Servants.

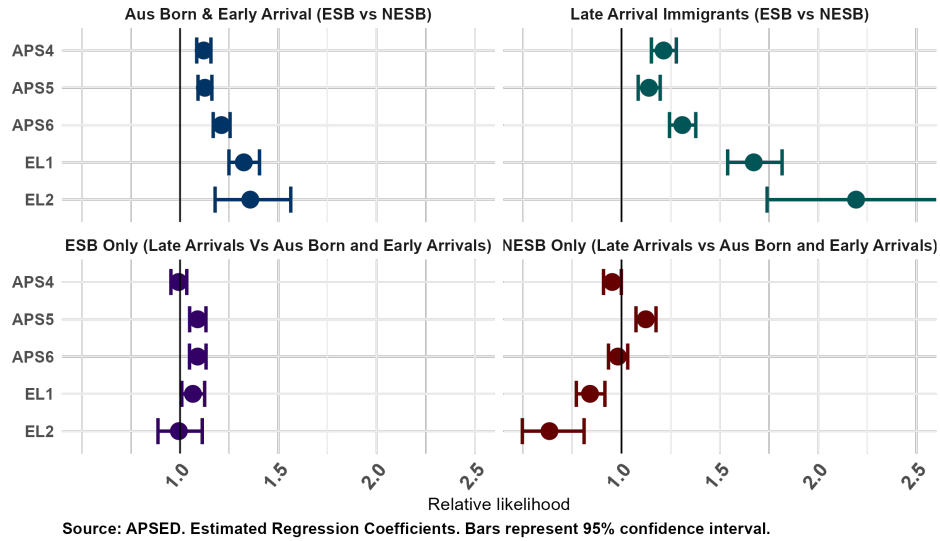

Figure 3 .6: Promotion by Australian born/raised and NESB status

[17]We chose this age because those who arrive in Australia aged five or younger are educated in Australia under a common national curriculum. They will almost certainly speak English with an Australian accent. We also tested whether the results changed if we use a later cut-off of age 10. Those results are consistent with what we report here.

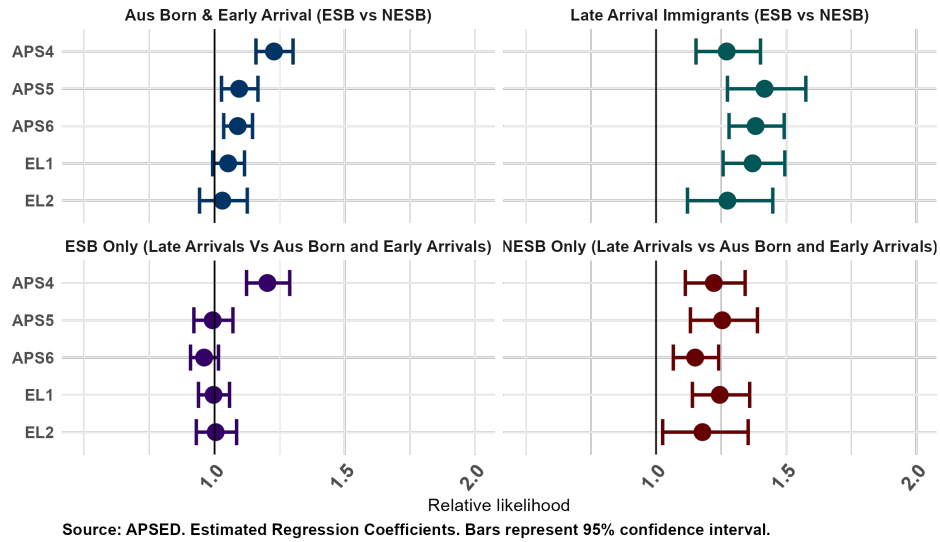

Figure 3 .7: Separation by Australian born/raised and NESB status

The upper right hand panel of Figure 3 .6 shows that among immigrants who arrived in Australia after the age of five, those with an English speaking background have a significantly higher likelihood of being promoted than those of non-English speaking background. This likelihood becomes significantly larger again at the most senior levels, with ESB late-arrival immigrants having more than double the prospects of promotion relative to NESB late-arriving immigrants at the EL2 level, controlling for all other observable characteristics. This may be evidence of a language penalty. However, without more detailed information about fluency, it is hard to separate language and cultural differences when comparing late-arriving migrants from English speaking and non-English speaking countries given the potential for very large cultural differences.

The bottom left panel of Figure 3 .6 shows that at all levels of seniority the likelihood of promotion of ESB staff are similar whether they were born in Australia or immigrated before the age of six, or if they arrived later. While the differences at APS5 and APS6 levels are statistically significant, they are small and there are no statistically significant differences at other levels. This suggests that the act of immigrating itself does not hinder promotion prospects in the APS.

Figure 3 .7 looks at the probability of separation for the same population splits as Figure 3 .6. There are only small differences between the probability of separation for ESB and NESB individuals who are either born in Australia or who arrived before the age of 6. If separation is a proxy for prospects outside the APS, this suggests that the promotion prospects for early arrival NESB might be better in the wider job market. There are no differences, except at the APS4 level, in separation probabilities for ESB individuals based upon whether they migrated after the age of 5 or whether they were born in Australia or arrived at an early age. For the NESB group, late arrival immigrants are more likely to separate than those who arrived before the age of 6 (or who were born in Australia), consistent with their lower promotion probabilities. For late arrival immigrants, the ESB are more likely to separate than the NESB at all levels. For all four comparisons, there are not many differences across different APS levels.

The poorer promotion prospects of NESB individuals is not easily explained by language difficulties or cultural assimilation. Might it be due to racial factors? 'White Australia' was legislated policy from 1901 and was only completely dismantled with the passage of the *Racial Discrimination Act 1975*. Anti-Asian sentiment has long been a part of the landscape in Australia and it worsened during COVID-19, see Biddle et al. (2020).

The Gazette data, described in section 3 .4 above indicate that staff with East Asian/Pacific and South Asian names make up around 9% of APS level promotions but only around 2% of SES promotions. To investigate the degree to which being Asian, as opposed to simply coming from a non-English speaking background, affects our results we compare promotion prospects for Australian-born ESB staff to those born in Asia and

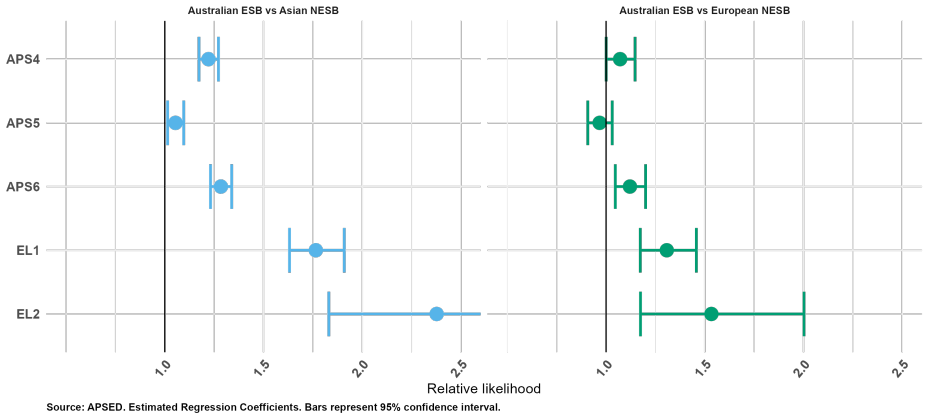

Figure 3 .8: Promotions, by continent of birth and language background

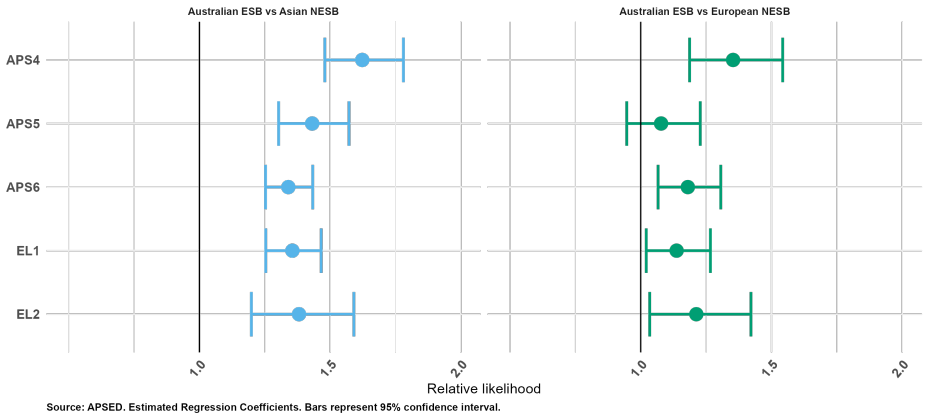

Figure 3 .9: Separations, by continent of birth and language background

non-Asian NESBs. 'Asia' here is defined as the Australian standard classification of countries 5101 to 7211, see Australian Bureau of Statistics (2022), spanning South East Asia, North East Asia and Southern and Central Asia. Recall that our data have no information on race or ethnicity so we use country of birth and language background to proxy 'Asian-ness'.

Figure 3 .8 shows several interesting patterns. First, Asian-born individuals of English speaking background are less likely than Australian-born English speakers to be promoted at every level except the APS5 and EL2 levels. Comparing the upper left hand panel of Figure 3 .8 to the bottom left panel of Figure 3 .6, there seems to be a penalty for English-speaking background immigrants born in Asia relative to other ESB immigrants. This group is quite mixed. It includes Anglo-looking Australians who were born to Australian parents overseas but also includes Singaporeans (or Malaysians, Hong Kongese, etc.) of various ethnic backgrounds who grew up speaking English. The results here could be due to cultural or racial differences for some people in this group.

Comparing the two left-hand side panels of Figure 3 .8, we can see little difference in promotion prospects for Asian ESB and Asian NESB who arrived in Australia before the age of six. This is further evidence that the poorer promotion prospects of Asian NESB who arrive in Australia are not driven by language differences. Comparing the two right hand side panels of Figure 3 .8, the promotion prospects of NESB born in Asia are much worse than those born in Europe. A direct comparison of Asian NESB to European NESB shows statistically significant differences (with European NESB having better promotion prospects) for promotion from the APS4, APS6 and EL1 levels.

NESBs who arrive from Asia before the age of 6 face a promotion penalty relative to Australian ESBs. They have worse promotion prospects at all levels, but the differences are only statistically significant at the APS6 and EL1 levels. The point estimates that generate the bottom left panel in Figure 3 .8 are quite similar to those for all NESBs who arrive in Australia before the age of 6 (the upper left hand panel of Figure 3 .6) which suggests that early arrival NESBs from Asia do not face any penalty relative to other early arrival NESBs.

For completeness, we include the results for separation in Figure 3 .9. The separation results for Asian-born NESB are similar to the overall results for NESB as reported in Figure 3 .7. European-born NESB are more likely to separate than Asian-born NESB, similar to their higher promotion prospects. But both groups separate at lower rates than Australian-born ESB.

The other comparisons have wide confidence intervals due to small sample sizes and are not particularly informative. Tables 3 .13 and 3 .14 and Tables 3 .22 and 3 .23 in Appendix B contain full coefficient results for the models which produce Figures 3 .8 and 3 .9.

Job family

We use job family data from the APSC to look at the possible role occupational segregation may play in APS promotion outcomes–Lind and Colquhoun (2021) and KPMG (2022) document and discuss the strength and persistence of occupational segregation in Australia.

Our approach of modelling promotion probabilities separately for each APS rank effectively controls for Analyst, Manager and Senior Manager status, since work-level expectations for these job titles across different agencies are set by the APSC through the Integrated Leadership System, a system of performance standards that is common across agencies. Nonetheless, there may be differences in roles even after controlling for rank. For example, while all staff at the EL1 level may be considered mid-managers, some staff may be concentrated in logistical or coordination roles that have limited prospects for career advancement. In contrast, other staff may be concentrated in policy formulation or advising that have better promotion prospects. We add information on job family, available only in the 2017-2020 period, to address this issue.

Job family refers to high-level groupings of roles that carry out similar types of work and hence require similar skills, capabilities and job-related knowledge. Job family categories are exclusive, meaning that any role falls into one and only one job family. It may be that some job families provide better promotion prospects than others and that employees from the different EEO categories are concentrated in those job families which provide poor promotion opportunities.

The APSC uses 18 Job Family categories such as Accounting and Finance, Communication and Marketing, Legal and Parliamentary services, Data and Research and Policy (which includes roles such as economists and policy analysts). Certain key roles such as Chief Data Officer are classed in the Senior Executive job family.

Many job families have an uneven gender representation. For example, 70 per cent or more of the staff in Service Delivery, Human Resources, Administration and Communications and Marketing are women. In addition, NESB staff make up a relatively high proportion (25 to 30 per cent) of staff in ICT and Digital Services, Accounting and Finance and Legal and Parliamentary.

The job family data are only available for about 70 per cent of staff and only from 2017. We begin by re-estimating our baseline promotion and separation models over this shorter time period and reduced sample to determine whether the estimates for the 2018-2020 period are the same as for the 2002-2020 period (see Tables 3 .15 and 3 .24). We need 2017 data to estimate whether someone is promoted or separated in 2018. The main difference in the coefficient estimates is that females are now more likely to be promoted than males at every level except APS5 to APS6. Promotion prospects for women have clearly changed over time and we explore this further in the next subsection.

Looking at the results for separation in Table 3 .24, we now see that staff with disabilities are more likely to separate at all levels in sharp contrast with the baseline results of Figure 3 .3. The patterns of separation for women have also changed. Women in this more recent period are less likely to separate than men at the APS6 level and higher and are not different than men at the APS4 and APS5 levels.

We then add job family fixed effects (see Tables 3 .16 and 3 .25) into these two models. Comparing Figures 3 .10 and 3 .11, we find no evidence that occupational crowding and segregation are driving the NESB outcomes, with the coefficients almost unchanged when we add job family fixed effects. There is a small decrease in the size of the NESB promotion effect for promotion from EL2 to SES level but the overall conclusions do not change. The distribution of NESB staff across job families do not explain their poor promotion prospects.

Promotion patterns for Indigenous Australians appear even worse at lower levels in this time period either with or without job family fixed effects.

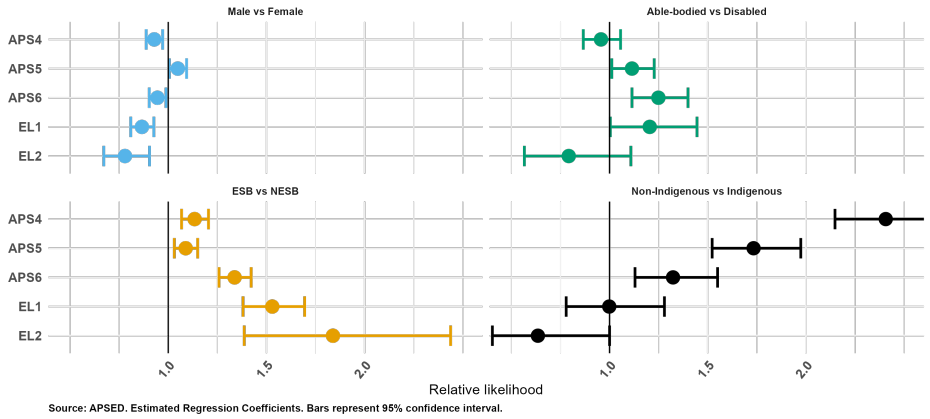

Figure 3 .10: Promotions, baseline model, 2018-2020

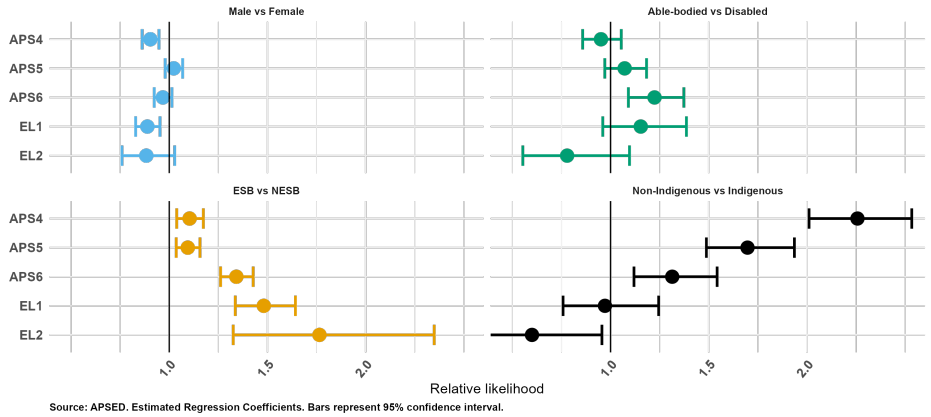

Figure 3 .11: Promotions, job family fixed effects, 2018-2020

Occupational segregation may play some role in different promotion prospects for males and females. For every level we see attenuation in the coefficients when we add job family fixed effects. The higher promotion prospects for women at APS6 and EL2 become statistically insignificant. The lower promotion prospects for women at APS5 also become statistically insignificant. Some of the differences we found earlier are thus coming from men and women being in different job families and once we control for this, there is not much difference in promotion prospects at APS5, APS6 and EL2 levels. This may be endogenous - women may select into those job families where they know that their promotion prospects are better. Women are still more likely to be promoted than similar men, in this 2018-2020 time period, from APS4 and EL1.

Women make up around 70 per cent in jobs families such as administration, human resources and customer support. Women also make up over 60 per cent of staff in job families with the highest probabilities of promotion from EL2 to SES. These are the Policy and Legal and Parliamentary job families.

Unfortunately the job family data are only available for the 2017-2020 period and we cannot tell to what degree these issues explain the results from earlier years. Our preferred estimates remain those that use the entire 19 year sample.[18]

The interaction between gender and other EEO characteristics

Figures 3 .12 and 3 .13 show promotion probabilities for staff with disabilities (relative to those who do not report disability), Indigenous (relative to non-Indigenous) and NESB (relative to ESB) split by gender. In the United States (Lewis and Allee 1992) females within EEO categories had worse outcomes than similar males. In Australia, this is not the case. There is almost no difference in the promotion prospects for NESB or staff with disabilities when we split by gender. This is an interesting result and suggests that gender is not playing a large role in the poorer employment prospects for those with disabilities or the NESB and that the increases in promotion probability for women overall have largely bypassed women with disability and NESB women.

If we reproduce Figure 3 .6 split by gender, we find similar patterns for men and women when we consider ESB and NESB split by whether they migrated early in life or late in life to Australia. These results are presented in Figures 3 .18 through 3 .21 in Appendix E. Similarly for separation, we find almost no differential effects for those with disabilities and NESB or Indigenous individuals by gender. We also find that the effect of skills on promotion or separation probabilities are not much different by gender.[19]

[18] Estimates for the separation model are included in Appendix Tables 3 .24 and 3 .25. The small number of separations over this time period results in all comparisons being statistically insignificant so we have not included these figures.

[19] These results are available from the authors upon request. We estimated versions of our models where we interacted EEO characteristics with the skills and other control variables and the marginal effects from those models are nearly identical to the ones we report here. We thus prefer the more parsimonious model without interactions.

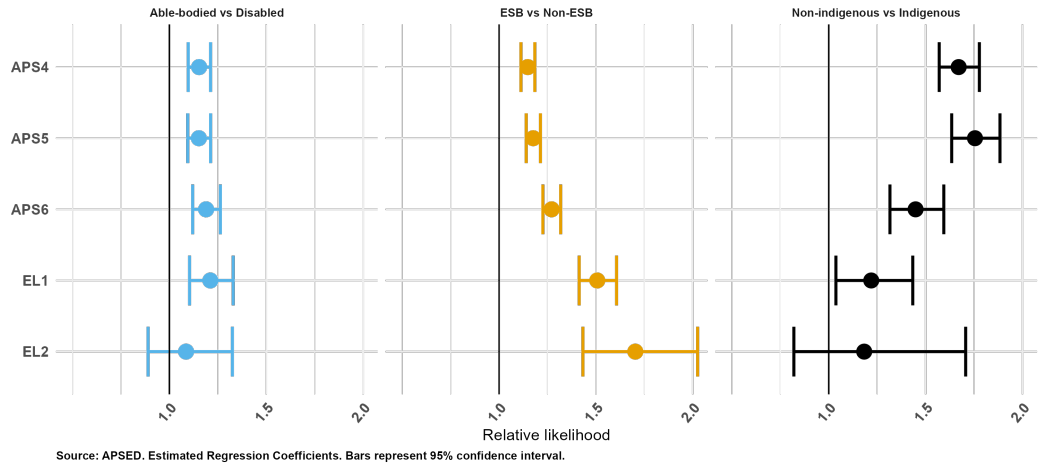

Figure 3 .12: Promotions, females, by EEO group

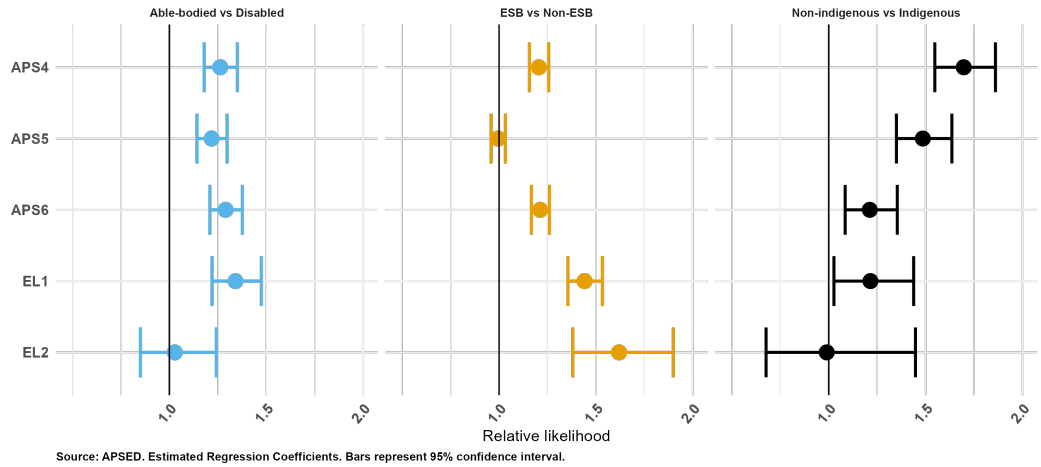

Figure 3 .13: Promotions, males, by EEO group

Changes in promotion prospects over time

We saw in Section 3 .7 above that the promotion probabilities for women relative to men became positive in the 2018-2020 period. Figures 3 .14 through 3 .17 show how the impact of female, disability, NESB and Indigenous evolve across the entire 19 years. We estimate the model on four-year windows and roll the window forward across time. The first estimate is for the 2001 - 2004 window and the last estimate is for the 2017-2020 window.

For women, promotion prospects relative to men have increased over time for most levels. For promotion from APS4, APS6 and EL1, there is a relatively steady trend over the entire time period. For APS5, promotion probabilities are higher relative to men in the last 4 years of data, but dipped between 2010 and 2015. There is a similar dip between 2007 and 2015 for promotion from EL2 to SES ranks, but throughout the time period, women's promotion prospects were always at least as good as those of similar men.

Recall from section 3 .2 that the *Workplace Gender Equality Act 2012* came into force in 2012. The timing of this appears to match an uptick in women's promotion prospects relative to men with notably higher probabilities of promotion for women in the points from 2015 onward where most of the data would have been affected by this act. Recall that the 2015 estimate incorporates data from 2012-2015.

We find no clear pattern for the relative promotion probabilities of staff with a disability. At the APS4 level, there is steady improvement over time with promotion probabilities for those with a disability catching up to those without a disability by the end of the period. For the other levels, the trend is downward or flat in the early period with perhaps some sign of improvement towards the last five years. There is no discernible impact from the 2005 amendments to the Disability Discrimination Act that were intended to improve employment prospects for staff with disability. There is perhaps a small improvement in employment probabilities for staff with disability coming from the 2013 Commissioner's directions (see section 3 .2 above) with increases in employment prospects for those reporting disability, relative to those who do not, at most levels apparent from 2017 onward.

For NESB, relative promotion probabilities from APS4 and APS5 are mostly constant over the time period. For all of the higher levels, the promotion probabilities of NESB relative to NESB have decreased across the two decades covered by our data. There is no visible impact from the 2013 amendments to the Public Service Act which required departments to improve the degree to which the public service reflected the diversity of the Australian population.

Akin to the results for those with a disability, we find no clear pattern for the relative promotion probabilities of Indigenous Australians. Promotion prospects at the lowest level, APS4, have clearly worsened since 2010. This is the level that has the highest number of Indigenous APS employees. Promotion prospects from APS5 and APS6 are poor and remain so across all 20 years. For most years, promotion prospects from EL1 and EL2 are not statistically different than zero. For promotion from EL1 to EL2, there was deterioration between 2004 and 2011 and improvement since then back to parity with the non-Indigenous. For promotion from EL2 to SES there seems to be some improvement but small sample sizes make it difficult to claim strong results.

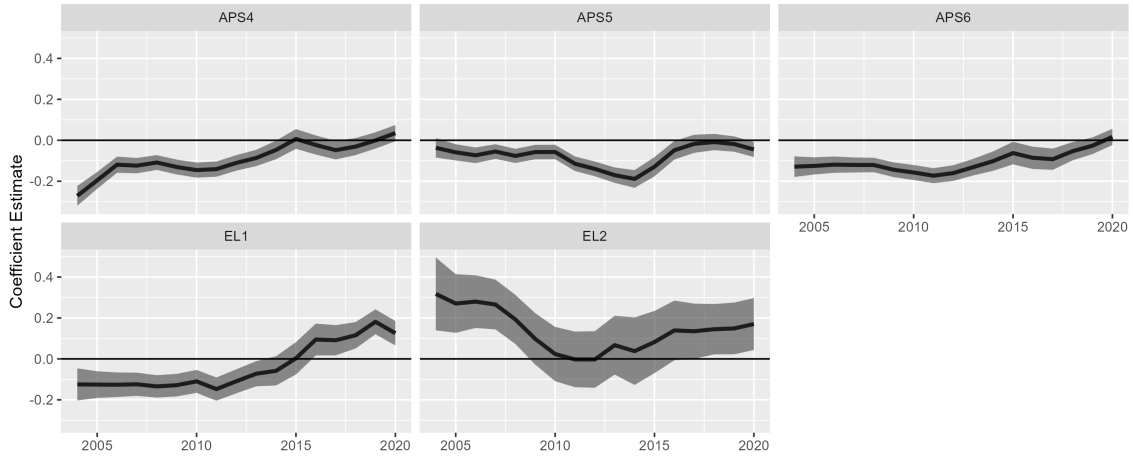

Figure 3 .14: Females promotion relative to males: changes in coefficient over time
Estimates based upon rolling 4-year window from 2001-2004 to 2017-2020

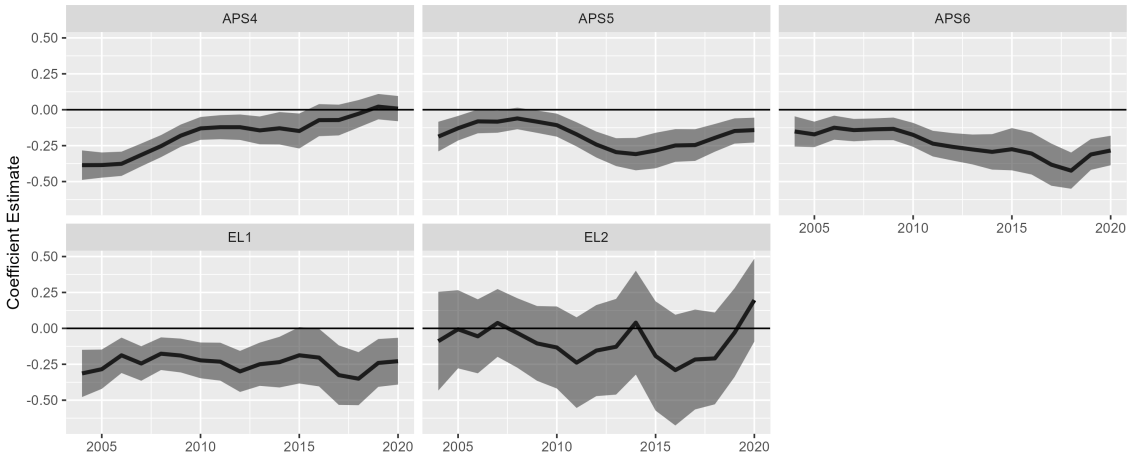

Figure 3 .15: Disability promotion relative to non-disability: changes in coefficient over time
Estimates based upon rolling 4-year window from 2001-2004 to 2017-2020

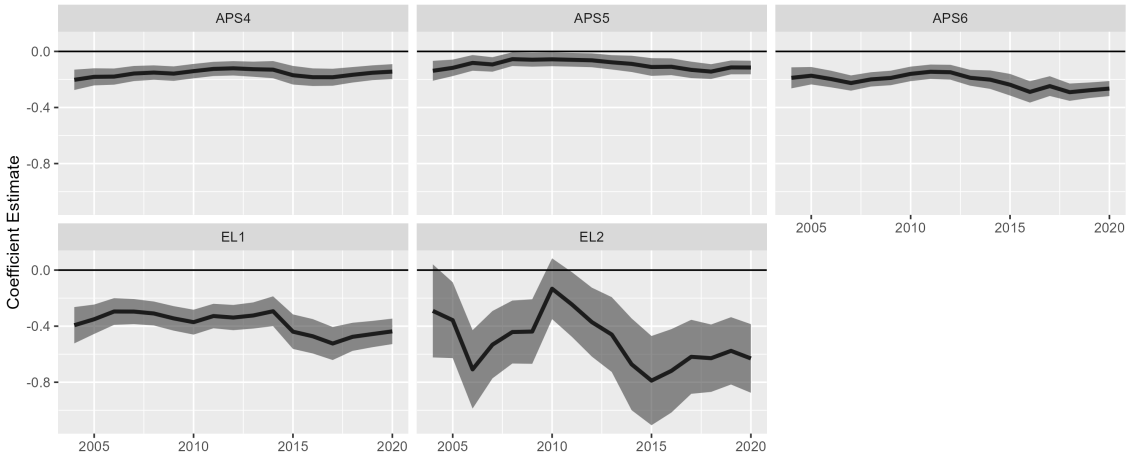

Figure 3 .16: NESB promotion relative to ESB: changes in coefficient over time
Estimates based upon rolling 4-year window from 2001-2004 to 2017-2020

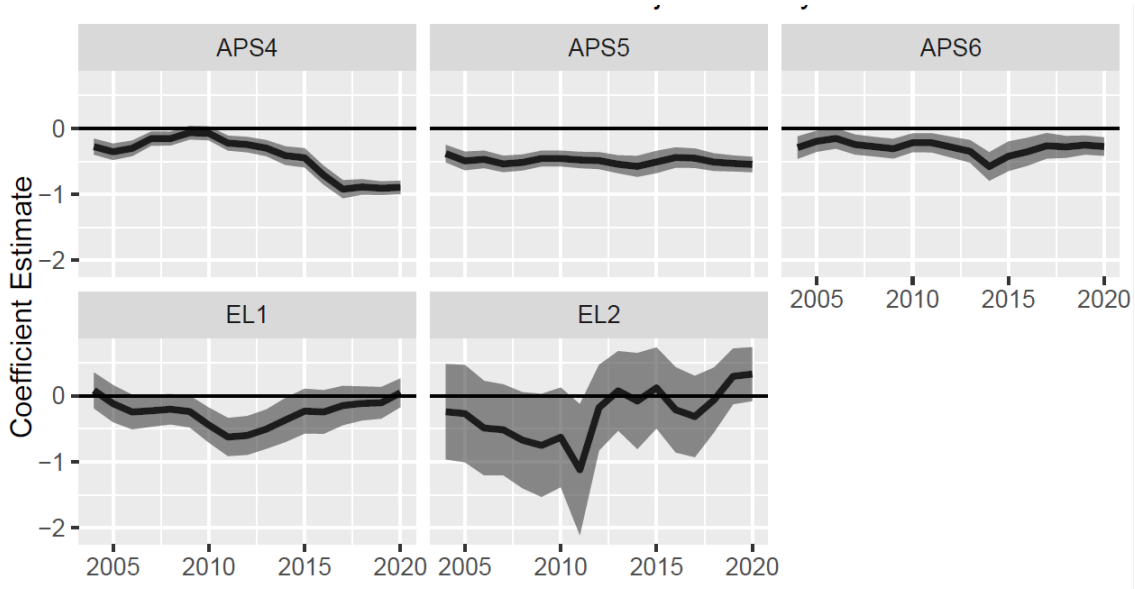

Figure 3 .17: Indigenous promotion relative to non-Indigenous: changes in coefficient over time
Estimates based upon rolling 4-year window from 2001-2004 to 2017-2020

3 .8 Discussion and conclusion

We examine the probabilities of promotion and separation in the Australian Public Service (APS) for four groups which are under-represented in the senior ranks. We use the universe of the APS' personnel database and consider promotion and separation through separate models for each of five different levels of seniority.

For women, we find that in the 2002-2015 period they are less likely to be promoted than similar men after controlling for a wide range of observable characteristics at the four lowest levels of rank. However, for promotion at the very top level, from EL2 to SES, women have been consistently more likely to be promoted than similar men. At all levels, the relative promotion prospects of women have increased dramatically over time. In the later years of our data, particularly in the 2017-2020 period, women are at least as likely as similar men to be promoted at all levels. At the two most senior levels, EL1 and EL2, they are more likely than similar men to be promoted. We find no evidence of a 'glass ceiling' for women. Using data for the three most recent years only, it appears that some of the better promotion prospects for women may come from women being in job families where there are more promotions. Women are still more likely to be promoted than similar men, but the differences diminish when we control for occupational segregation.

The story is quite different for those who identify as being from a non-English speaking background (NESB). NESB are less likely to be promoted than similar ESB individuals and the gap in promotion prospects increases as we consider higher levels of rank in the public service. Promotion prospects for the NESB appear to have gotten worse over time compared to similar individuals from an English-speaking background. Other than a general policy that the public service should reflect the diversity of the Australian population, the APS does not have targets or other types of affirmative action for this group.

The NESB results are only partially explained by language fluency and cultural assimilation. When we consider NESB who are born in Australia or who arrived at a young age, we find smaller, but still statistically significant differences in relative probability promotions compared to Australian-born or immigrant ESB. Asian-born NESB who migrate here before the age of six appear to do about as well as other migrants who arrive before the age of six. However, Asian-born NESB who arrive after the age of five have worse promotion prospects than non-Asian NESB who arrive after the age of five. Asian-born NESB who arrive before the age of six have similar promotion prospects to Asian-born ESB. These two results suggests that there is some 'Asian penalty' that is not related to language or cultural assimilation. Immigration itself does not hamper promotion prospects, as ESB individuals arriving after six years of age face similar promotion probabilities to their native-born counterparts.

The results for NESB employees provide a particularly rich starting point for testing specific theories of labour market discrimination, including statistical discrimination (Becker (1971)), taste-based explanations (Arrow (1971)) or theories based around club and class membership (see for example Das (2013)). Without formally testing each of the models, which is beyond the scope of this paper, a few remarks can be made. First, our results appear inconsistent with standard versions of statistical discrimination, which posit that employers engage in discrimination rationally in response to incomplete information in which they attribute average group characteristics to individuals. Given the gap in promotion rates widen with career length and job tenure, when information asymmetries would presumably be diminishing, our results look incompatible with a purely statistical-based explanation. Delineating between taste-based and more institutional explanations is a much more difficult exercise and likely to require richer data on observables (e.g., employer or interviewer characteristics) than was available for this study, but would be a valuable future research direction.

For staff with disabilities, they are less likely to be promoted than similar individuals who do not report a disability but the gap narrows as we move up in rank. There does seem to have been some narrowing in the gap in the relative probability of promotion over time, particularly since 2017. For Indigenous people we find similar results but the gap in promotion prospects is larger than for those with a disability. Also, at the lower levels of the public service, the gap in promotion probabilities has either increased or stayed the same over time. Unlike in the US, we do not find that the decreased promotion probabilities for NESB, Indigenous or those with disability differ by gender.

We examine separation and find that Indigenous Australians are much more likely to separate from the public service than other groups. This could reflect their poor promotion prospects or a feeling of not fitting in with the

dominant culture. We find that the other three groups are less likely to separate from the public service at all levels. However, the relative probabilities of separation for the groups get smaller as we move up in levels and, at the top level, women and staff with disabilities are more likely to separate than men or those who do not report a disability, respectively. In more recent years, staff with disabilities are more likely to separate from the public service than those without and women are more likely to separate than similar men. Interestingly, separation probabilities for these two groups have increased at the same time that their promotion prospects have improved.

It is somewhat puzzling that we do not see higher rates of separation from the NESB group given their low internal promotion prospects. It could be due to the employment barriers they face outside of the public service (Booth et al. 2012; Adamovic and Leibbrandt 2023). It could be that they value other job characteristics inside the public service more highly than they value higher remuneration or promotion outside the public service. Or, it could be that unobservable human capital characteristics explain both the low promotion prospects inside the public service and the low relative rates of separation. More data on what happens to those who leave the public service or information about individual performance reviews from inside the public service would help to disentangle these competing explanations.

The general upward trend in women's relative promotion probabilities suggests that concerted effort and attention over time coupled with dedicated affirmative action policies can raise promotion prospects for EEO cohorts. Notably, the period in which female promotion prospects improved most strongly is after 2012-13, around the time when the *Workplace Gender Equality Act 2012* was passed and the Workplace Gender Equality Agency established. For those with disabilities, relative promotion prospects have increased, most visibly at the two lowest levels, APS4 and APS5. The timing of these increases suggests that there may be some effect of explicit public service focus on the promotion prospects of people with disabilities through the Commissioner's Directions of 2013.

In contrast, the NESB results suggest that in the absence of concerted effort and dedicated policies, outcomes have not improved. To the degree to which these poor relative promotion prospects are driven by "being foreign" or "looking Asian" as opposed to any characteristics related to productivity, this is a problem for the APS. It is failing to reflect the rich diversity of Australia. Further, if poor outcome prospects lead to reduced work effort, as in Karachiwalla and Park (2016) or Deserranno et al. (2021), the Australian community is being under-served by the APS. More research and focus on this group to find out what is going on would be desirable.

There is a broad sociological literature on workplace inequality that hypothesises mechanisms which can generate the kind of promotion gaps that we observe. This includes organisational inertia and relative power (e.g. Stainback et al. (2010)), both of which may explain the results we find for NESB staff. The White Australia policy, eliminated in the 1970s through various measures including the *Racial Discrimination Act 1975*, resulted in an Australia where the Asian population was less than one half of one percent.[20] Large numbers of NESB staff in the APS is a relatively recent phenomena and organisations may be slow to evolve and NESB staff may not have power within the organisation.

Access to informal networks, mentorship opportunities or unconscious bias in hiring practices could all explain our results to some degree. Faulkner and Lahn (2020), in their qualitative study, point to the importance of mentors in the positive experiences of Indigenous staff in the APS. Kanter (1977) explained gender relations in companies through the lens of tokenism. Tokenism is likely an important factor in explaining the experiences of NESB staff, Indigenous staff and staff with disabilities in the APS. Our data do not allow us to test any of these possible explanations. Our results are likely driven by a mixture of factors.

We conclude by noting two important caveats to our results. First, while we observe who gets promoted and who does not, we do not observe who applies for promotion. Differences in promotion prospects may arise through two mechanisms–the decision to apply and the promotion decision itself. We cannot say anything about the relative importance of these two channels. Second, we do not observe anything about the performance of individuals. Information on individual performance reviews would provide useful, additional information about people's performance in their current role that is likely related to promotion prospects.

[20] See `https://www.nma.gov.au/defining-moments/resources/white-australia-policy`

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Appendix 3 .A Summary statistics by APS level: 2002, 2010, 2020

Values in cells are proportions of individuals for whom the variable is equal to one. Standard deviations can be calculated as $p(1-p)$.

Variable	2002	2010	2020
Promotion	0.084	0.106	0.13
Separation	0.029	0.035	0.016
Female	0.645	0.687	0.681
Disability	0.079	0.069	0.056
Non-English Speaking Background	0.129	0.147	0.153
Indigenous	0.04	0.033	0.057
Accounting/Economics/Finance degree	0.039	0.04	0.036
Bachelors or above	0.194	0.214	0.154
Graduate Program	0.061	0.07	0.104
Central Agency experience	0.025	0.032	0.019
Part time	0.133	0.19	0.212
Maternity leave	0.015	0.029	0.018
Arrived age 5 or younger	0.133	0.129	0.126
Born in Australia	0.655	0.676	0.632
Number of observations	34400	37863	31217

Table 3 .2: APS4 Summary Statistics

Variable	2002	2010	2020
Promotion	0.189	0.166	0.171
Separation	0.027	0.037	0.022
Female	0.503	0.579	0.614
Disability	0.061	0.052	0.049
Non-English Speaking Background	0.121	0.143	0.158
Indigenous	0.03	0.029	0.033
Accounting/Economics/Finance degree	0.067	0.053	0.045
Bachelors or above	0.334	0.316	0.248
Graduate Program	0.139	0.127	0.16
Central Agency experience	0.049	0.056	0.042
Part time	0.069	0.098	0.123
Maternity leave	0.009	0.022	0.018
Arrived age 5 or younger	0.118	0.127	0.123
Born in Australia	0.604	0.667	0.646
Number of observations	18708	27274	26316

Table 3 .3: APS5 Summary Statistics

Variable	2002	2010	2020
Promotion	0.1	0.093	0.086
Separation	0.033	0.037	0.026
Female	0.477	0.545	0.585
Disability	0.067	0.054	0.045
Non-English Speaking Background	0.126	0.15	0.171
Indigenous	0.018	0.017	0.021
Accounting/Economics/Finance degree	0.076	0.064	0.058
Bachelors or above	0.467	0.451	0.389
Graduate Program	0.136	0.124	0.156
Central Agency experience	0.054	0.06	0.054
Part time	0.08	0.118	0.139
Maternity leave	0.01	0.024	0.019
Arrived age 5 or younger	0.127	0.141	0.138
Born in Australia	0.616	0.655	0.658
Number of observations	26699	37469	38533

Table 3 .4: APS6 Summary Statistics

Variable	2002	2010	2020
Promotion	0.06	0.049	0.049
Separation	0.032	0.035	0.024
Female	0.396	0.482	0.54
Disability	0.066	0.056	0.039
Non-English Speaking Background	0.105	0.136	0.157
Indigenous	0.011	0.015	0.015
Accounting/Economics/Finance degree	0.118	0.093	0.084
Bachelors or above	0.594	0.543	0.506
Graduate Program	0.173	0.154	0.196
Central Agency experience	0.095	0.094	0.096
Part time	0.064	0.102	0.124
Maternity leave	0.01	0.022	0.017
Arrived age 5 or younger	0.117	0.138	0.135
Born in Australia	0.617	0.667	0.68
Number of observations	16909	29996	29605

Table 3 .5: EL1 Summary Statistics

Variable	2002	2010	2020
Promotion	0.025	0.019	0.024
Separation	0.04	0.042	0.029
Female	0.303	0.394	0.492
Disability	0.063	0.052	0.036
Non-English Speaking Background	0.078	0.099	0.112
Indigenous	0.01	0.01	0.013
Accounting/Economics/Finance degree	0.146	0.117	0.099
Bachelors or above	0.693	0.638	0.604
Graduate Program	0.177	0.179	0.212
Central Agency experience	0.114	0.127	0.126
Part time	0.037	0.076	0.077
Maternity leave	0.005	0.014	0.01
Arrived age 5 or younger	0.11	0.121	0.109
Born in Australia	0.597	0.652	0.689
Number of observations	8514	13892	12834

Table 3 .6: EL2 Summary Statistics

Variable	2002	2010	2020
Female	0.29	0.375	0.489
Disability	0.063	0.058	0.048
Non-English Speaking Background	0.061	0.071	0.064
Accounting/Economics/Finance degree	0.223	0.177	0.141
Indigenous	0.017	0.007	0.016
Bachelors or above	0.778	0.752	0.651
Central Agency experience	0.218	0.258	0.268
Graduate Program	0.227	0.252	0.295
Part time	0.014	0.026	0.034
Maternity leave	0.002	0.005	0.004
Arrived age 5 or younger	0.092	0.094	0.073
Born in Australia	0.678	0.716	0.728
Number of observations	1740	2725	2834

Table 3 .7: SES Summary Statistics

Appendix 3 .B Logistic Regression Results

For all Tables in this Appendix, values in cells are coefficients from logistic regression. Standard errors are clustered at the level of the individual. Significance at the 10, 5 and 1 per cent levels are indicated by *, ** and *** respectively. All regressions include a dummy for part time status, whether an individual is always part time and a continuous variable indicating the rolling fraction of part time work.

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0938***	-0.0720***	-0.102***	-0.0448**	0.153***
Disabled	-0.178***	-0.163***	-0.210***	-0.241***	-0.0550
NESB	-0.156***	-0.0901***	-0.213***	-0.383***	-0.499***
Indigenous	-0.513***	-0.496***	-0.286***	-0.195***	-0.0821
Skills					
Accounting/Economics/Finance degree	-0.0872***	-0.112***	0.0772***	0.00744	0.0711
Bachelor or above	0.467***	0.527***	0.210***	0.121***	-0.110***
Graduate program participant	0.0730***	-0.269***	0.0690***	-0.0368*	0.179***
Central agency experience	0.615***	0.355***	0.495***	0.326***	0.674***
Controls					
Maternity leave	-0.750***	-0.628***	-0.526***	-0.480***	-0.915***
Time at level	-0.307***	-0.226***	-0.118***	-0.0828***	-0.0579***
Time at level squared	0.00950***	0.00701***	0.00279***	0.00239***	0.00137**
Age	0.0809***	0.0836***	0.174***	0.232***	0.284***
Age squared	-0.00121***	-0.00125***	-0.00229***	-0.00280***	-0.00318***
Year FEs	YES	YES	YES	YES	YES
Observations	644442	450854	636706	484728	222233
Pseudo R^2	0.130	0.084	0.058	0.037	0.038

Table 3 .8: Promotion, Baseline model 2002-2020

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0982***	-0.0481***	-0.0813***	-0.0177	0.138***
Disabled	-0.168***	-0.163***	-0.213***	-0.243***	-0.0689
NESB	-0.114***	-0.119***	-0.191***	-0.281***	-0.305***
Indigenous	-0.515***	-0.499***	-0.279***	-0.191**	-0.0819
Skills					
Accounting/Economics/Finance degree	-0.0871***	-0.0830***	0.0927***	0.00658	0.0737
Bachelor or above	0.489***	0.536***	0.221***	0.130***	-0.101**
Graduate program participant	0.0783***	-0.257***	0.0763***	-0.0327	0.166***
Central agency experience	0.610***	0.360***	0.502***	0.332***	0.670***
Controls					
Maternity leave	-0.773***	-0.635***	-0.536***	-0.492***	-1.036***
Time at level	-0.301***	-0.213***	-0.105***	-0.0723***	-0.0490***
Time at level squared	0.00927***	0.00646***	0.00233***	0.00190***	0.000758
Age	0.0815***	0.0804***	0.176***	0.228***	0.274***
Age squared	-0.00120***	-0.00121***	-0.00233***	-0.00277***	-0.00307***
Year FEs	YES	YES	YES	YES	YES
Observations	559770	393238	547514	419152	195804
Pseudo R^2	0.128	0.080	0.056	0.034	0.037

Table 3 .9: Promotion, 2002-2020 (Sample excludes those who came to Australia after age 5)

3

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0653*	-0.214***	-0.230***	-0.247***	0.271**
Disabled	-0.272***	-0.175**	-0.195**	-0.241*	0.0831
NESB	-0.194***	-0.131***	-0.269***	-0.514***	-0.785***
Indigenous	-0.355	0.240	-0.471	-0.444	0
Skills					
Accounting/Economics/Finance degree	-0.0664	-0.191***	0.0317	0.0200	0.0167
Bachelor or above	0.356***	0.427***	0.109***	0.0535	-0.163
Graduate program participant	-0.0102	-0.378***	0.000857	-0.102	0.293*
Central agency experience	0.660***	0.311***	0.455***	0.287***	0.738***
Controls					
Maternity leave	-0.528***	-0.587***	-0.487***	-0.416	0.241
Time at level	-0.343***	-0.305***	-0.187***	-0.151***	-0.130***
Time at level squared	0.0109***	0.0106***	0.00514***	0.00558***	0.00588***
Age	0.0604***	0.0687***	0.160***	0.238***	0.377***
Age squared	-0.000993***	-0.00115***	-0.00207***	-0.00287***	-0.00416***
Year FEs	YES	YES	YES	YES	YES
Observations	84672	57616	89192	65576	26419
Pseudo R^2	0.143	0.116	0.077	0.058	0.053

Table 3 .10: Promotion, 2002-2020 (Sample includes only those who came to Australia after age 5)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.106***	-0.0529***	-0.0981***	-0.0391**	0.155***
Disabled	-0.169***	-0.158***	-0.204***	-0.256***	-0.115
Arrived age 6 or more	-0.00701	0.0857***	0.0856***	0.0633*	-0.00598
Indigenous	-0.505***	-0.491***	-0.284***	-0.203***	-0.0756
Skills					
Accounting/Economics/Finance degree	-0.0828***	-0.0896***	0.0850***	0.0144	0.0795
Bachelor or above	0.494***	0.543***	0.224***	0.131***	-0.102**
Graduate program participant	0.0622***	-0.278***	0.0767***	-0.0378*	0.175***
Central agency experience	0.605***	0.348***	0.495***	0.331***	0.674***
Controls					
Maternity leave	-0.768***	-0.601***	-0.529***	-0.469***	-0.936***
Time at level	-0.309***	-0.225***	-0.119***	-0.0841***	-0.0612***
Time at level squared	0.00958***	0.00698***	0.00283***	0.00243***	0.00145**
Age	0.0839***	0.0813***	0.172***	0.233***	0.284***
Age squared	-0.00123***	-0.00121***	-0.00226***	-0.00280***	-0.00317***
Year FEs	YES	YES	YES	YES	YES
Observations	548278	384803	538746	417258	199445
Pseudo R^2	0.130	0.083	0.058	0.035	0.037

Table 3 .11: Promotion, 2002-2020 (Sample excludes those from NESB)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0269	-0.183***	-0.133***	-0.0995*	0.137
Disabled	-0.253***	-0.219***	-0.272***	-0.103	0.650**
Arrived age 6 or more	-0.0485*	0.116***	-0.0187	-0.175***	-0.456***
Indigenous	-0.584**	-0.371*	-0.182	0.114	-0.466
Skills					
Accounting/Economics/Finance degree	-0.0725*	-0.156***	0.0710*	-0.0251	-0.0357
Bachelor or above	0.341***	0.419***	0.0932***	0.0167	-0.221
Graduate program participant	0.109***	-0.235***	0.0287	-0.0192	0.236
Central agency experience	0.662***	0.394***	0.501***	0.290***	0.662***
Controls					
Time at level	-0.3024 ***	-0.2475 ***	-0.1036 ***	-0.0687 ***	-0.0083
Maternity leave	-0.641***	-0.800***	-0.500***	-0.575**	-0.666
Time at level	-0.291***	-0.222***	-0.104***	-0.0678***	-0.00609
Time at level squared	0.00888***	0.00703***	0.00250***	0.00190*	0.000138
Age	0.0592***	0.102***	0.189***	0.222***	0.286*
Age squared	-0.00101***	-0.00160***	-0.00257***	-0.00283***	-0.00338**
Year FEs	YES	YES	YES	YES	YES
Observations	96164	66051	97960	67470	22788
Pseudo R^2	0.130	0.095	0.062	0.040	0.045

Table 3 .12: Promotion, 2002-2020 (Sample includes only those from NESB)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.129***	-0.0422***	-0.0889***	-0.0287	0.153***
Disability	-0.201***	-0.142***	-0.233***	-0.249***	-0.0881
Born in Australia	0.0686*	-0.0334	0.114***	0.268***	0.428**
Indigenous	-0.531***	-0.494***	-0.295***	-0.179**	-0.0222
Skills					
Accounting/Economics/Finance degree	-0.0574*	-0.0686**	0.0871***	0.0128	0.0374
Bachelor or above	0.494***	0.570***	0.246***	0.180***	0.0283
Graduate program participant	0.0569***	-0.239***	0.113***	-0.0157	0.145***
Central agency experience	0.582***	0.350***	0.478***	0.332***	0.620***
Controls					
Maternity leave	-0.733***	-0.626***	-0.541***	-0.508***	-1.119***
Time at level	-0.299***	-0.195***	-0.0909***	-0.0487***	0.0374**
Time at level squared	0.00924***	0.00596***	0.00199***	0.00103**	-0.00229***
Age	0.0816***	0.0791***	0.184***	0.248***	0.263***
Age squared	-0.00121***	-0.00120***	-0.00245***	-0.00301***	-0.00310***
Year FEs	YES	YES	YES	YES	YES
Observations	404734	280344	394952	307738	140250
Pseudo R^2	0.132	0.079	0.056	0.036	0.037

Table 3 .13: Promotion, 2002-2020 (Sample includes only Australian ESB and Asian-born NESBs)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.118***	-0.0550***	-0.0966***	-0.0251	0.159***
Disability	-0.193***	-0.149***	-0.219***	-0.239***	-0.0873
Born in Australia	0.200***	0.0530**	0.250***	0.568***	0.866***
Indigenous	-0.538***	-0.497***	-0.296***	-0.181**	-0.0264
Skills					
Accounting/Economics/Finance degree	-0.0505*	-0.112***	0.0781***	0.0194	0.0486
Bachelor or above	0.472***	0.548***	0.237***	0.167***	0.0164
Graduate program participant	0.0587***	-0.233***	0.112***	-0.00880	0.142***
Central agency experience	0.600***	0.350***	0.472***	0.327***	0.630***
Controls					
Maternity leave	-0.729***	-0.643***	-0.526***	-0.527***	-1.125***
Time at level	-0.298***	-0.196***	-0.0894***	-0.0466***	0.0388**
Time at level squared	0.00926***	0.00602***	0.00186***	0.000944**	-0.00246***
Age	0.0818***	0.0809***	0.184***	0.244***	0.264***
Age squared	-0.00123***	-0.00124***	-0.00245***	-0.00297***	-0.00310***
Year FEs	YES	YES	YES	YES	YES
Observations	423434	294438	417982	322439	142683
Pseudo R^2	0.131	0.079	0.056	0.037	0.040

Table 3 .14: Promotion, 2002-2020 (Sample includes Australian ESB and Europe-born NESBs)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	0.0739**	-0.0474*	0.0566*	0.144***	0.249***
Disabled	0.0446	-0.108*	-0.222***	-0.186*	0.233
NESB	-0.126***	-0.0850**	-0.291***	-0.425***	-0.609***
Indigenous	-0.878***	-0.550***	-0.280***	0.00169	0.454*
Skills					
Accounting/Economics/Finance degree	-0.381***	-0.218***	0.0331	-0.147*	-0.0133
Bachelor or above	0.387***	0.379***	0.177***	0.0920**	-0.250***
Graduate program participant	0.0606*	-0.0927***	0.213***	-0.00788	0.0141
Central agency experience	0.732***	0.383***	0.416***	0.186***	0.637***
Controls					
Maternity leave	-0.612***	-0.606***	-0.617***	-0.508***	-0.986*
Time at level	-0.201***	-0.138***	-0.00722	0.0216	0.0616*
Time at level squaredl	0.00533***	0.00316***	-0.00221***	-0.00236***	-0.00431***
Age	0.0824***	0.114***	0.156***	0.232***	0.264***
Age squared	-0.00135***	-0.00164***	-0.00222***	-0.00299***	-0.00317***
Year FEs	YES	YES	YES	YES	YES
Observations	407409	282076	397709	308894	140370
Pseudo R^2	0.132	0.079	0.056	0.036	0.037

Table 3 .15: Promotion, baseline model 2018-2020

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	0.101***	-0.0225	0.0329	0.118***	0.124
Disabled	0.0501	-0.0692	-0.202***	-0.143	0.250
NESB	-0.0987**	-0.0902**	-0.294***	-0.393***	-0.568***
Indigenous	-0.814***	-0.529***	-0.273***	0.0290	0.511*
Skills					
Accounting/Economics/Finance degree	-0.166**	-0.109*	0.0316	-0.122	0.00449
Bachelor or above	0.278***	0.310***	0.191***	0.0957**	-0.184*
Graduate program participant	-0.0652*	-0.109***	0.164***	-0.0134	-0.0204
Central agency experience	0.480***	0.263***	0.146***	0.0742	0.455***
Controls					
Maternity leave	-0.616***	-0.597***	-0.623***	-0.507***	-0.995*
Time at level	-0.191***	-0.141***	-0.0135	0.0272*	0.0548*
Time at level squared	0.00521***	0.00339***	-0.00189***	-0.00257***	-0.00400**
Age	0.117***	0.133***	0.170***	0.228***	0.270***
Age squared	-0.00168***	-0.00182***	-0.00234***	-0.00295***	-0.00322***
Year FEs	YES	YES	YES	YES	YES
Job FEs	YES	YES	YES	YES	YES
Observations	94101	74535	108913	82001	35284
Pseudo R^2	0.141	0.068	0.052	0.030	0.041

Table 3 .16: Promotion, model with job family fixed effects, 2018-2020

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0342*	-0.00374	0.0162	0.00725	0.0890***
Disabled	-0.263***	-0.195***	-0.157***	-0.0915**	0.0923*
NESB	-0.289***	-0.185***	-0.170***	-0.154***	-0.112**
Indigenous	0.147***	0.326***	0.220***	0.190**	0.0937
Skills					
Accounting/Economics/Finance degree	-0.213***	-0.137***	-0.0670*	0.0225	0.153***
Bachelor or above	0.0432*	0.0367	-0.108***	-0.255***	-0.353***
Graduate program participant	0.202***	-0.0428	0.00510	-0.111***	-0.245***
Central agency experience	0.227***	0.0626	0.0582*	-0.0450	-0.0111
Controls					
Maternity leave	-5.041***	-4.682***	-5.195***	-4.718***	-4.637***
Time at level	0.0957***	0.148***	0.106***	0.100***	0.108***
Time at level squared	-0.00346***	-0.00400***	-0.00228***	-0.00173***	-0.00241***
Age	-0.128***	-0.176***	-0.181***	-0.206***	-0.114***
Age squared	0.00121***	0.00168***	0.00176***	0.00219***	0.00130***
Year FEs	YES	YES	YES	YES	YES
Observations	630354	408811	628030	495540	235566
Pseudo R^2	0.035	0.036	0.033	0.038	0.042

Table 3 .17: Separation, Baseline model 2002-2020

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0361*	0.00133	0.0239	0.0135	0.0885***
Disabled	-0.283***	-0.228***	-0.183***	-0.0984**	0.0869
NESB	-0.205***	-0.0902**	-0.0852***	-0.0507	-0.0295
Indigenous	0.141***	0.323***	0.236***	0.187**	0.0981
Skills					
Accounting/Economics/Finance degree	-0.222***	-0.148***	-0.0828**	0.00449	0.143***
Bachelor or above	0.0736***	0.0401*	-0.0888***	-0.253***	-0.355***
Graduate program participant	0.206***	-0.0396	0.00646	-0.104***	-0.220***
Central agency experience	0.209***	0.0346	0.0449	-0.0556*	-0.0244
Controls					
Maternity leave	-4.992***	-4.611***	-5.400***	-4.627***	-4.563***
Time at level	0.0977***	0.148***	0.112***	0.100***	0.106***
Time at level squared	-0.00359***	-0.00399***	-0.00250***	-0.00176***	-0.00241***
Age	-0.123***	-0.172***	-0.184***	-0.210***	-0.112***
Age squared	0.00117***	0.00165***	0.00181***	0.00226***	0.00130***
Year FEs	YES	YES	YES	YES	YES
Observations	547302	357341	540267	428551	207524
Pseudo R^2	0.034	0.035	0.033	0.038	0.042

Table 3 .18: Separation, 2002-2020 (Sample excludes those who came to Australia after age 5)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.00296	-0.0275	-0.0265	-0.0453	0.0911
Disabled	-0.103	0.0953	0.00925	-0.0492	0.129
NESB	-0.240***	-0.348***	-0.324***	-0.315***	-0.242***
Indigenous	0.434	1.049**	-0.358	0.525	0
Skills					
Accounting/Economics/Finance degree	-0.138	-0.0829	0.00514	0.103	0.195*
Bachelor or above	-0.0945	0.0658	-0.211***	-0.216***	-0.317***
Graduate program participant	0.104	-0.116	-0.0543	-0.178**	-0.511***
Central agency experience	0.395**	0.335**	0.173*	0.0594	0.117
Controls					
Maternity leave	0	0	-4.042***	0	0
Time at level	0.0784***	0.149***	0.0746***	0.108***	0.128***
Time at level squared	-0.00267***	-0.00428***	-0.00115**	-0.00191***	-0.00271***
Age	-0.196***	-0.226***	-0.191***	-0.224***	-0.169***
Age squared	0.00192***	0.00217***	0.00177***	0.00220***	0.00167***
Year FEs	YES	YES	YES	YES	YES
Observations	81846	50718	87763	66138	27865
Pseudo R^2	0.032	0.040	0.036	0.037	0.046

Table 3 .19: Separation, 2002-2020 (Sample includes only those who came to Australia after age 5)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0233	0.00749	0.0311*	0.0187	0.0967***
Disabled	-0.272***	-0.241***	-0.171***	-0.109**	0.0827
Arrived age 6 or more	-0.185***	0.00728	0.0409	0.00394	-0.00430
Indigenous	0.127***	0.322***	0.225***	0.179**	0.0718
Skills					
Accounting/Economics/Finance degree	-0.201***	-0.146**	-0.0702*	0.0174	0.145***
Bachelor or above	0.0752***	0.0412*	-0.0908***	-0.253***	-0.344***
Graduate program participant	0.190***	-0.0367	-0.00480	-0.107***	-0.243***
Central agency experience	0.173***	0.0209	0.0307	-0.0701*	-0.0310
Controls					
Maternity leave	-4.949***	-4.563***	-5.355***	-4.879***	-4.542***
Time at level	0.101***	0.149***	0.109***	0.0993***	0.107***
Time at level squared	-0.00377***	-0.00400***	-0.00239***	-0.00169***	-0.00243***
Age	-0.122***	-0.169***	-0.172***	-0.200***	-0.108***
Age squared	0.00114***	0.00159***	0.00167***	0.00213***	0.00125***
Year FEs	YES	YES	YES	YES	YES
Observations	537014	349603	531474	426571	211508
Pseudo R^2	0.034	0.036	0.032	0.037	0.042

Table 3 .20: Separation, 2002-2020 (Sample excludes those from NESB)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.120*	-0.0697	-0.0686	-0.0762	0.00723
Disabled	-0.195*	0.158	-0.0646	0.0460	0.186
Arrived age 6 or more	-0.200***	-0.226***	-0.140***	-0.219***	-0.164*
Indigenous	0.609***	0.485	0.287	0.493	0.748*
Skills					
Accounting/Economics/Finance degree	-0.224**	-0.101	-0.0598	0.0418	0.195*
Bachelor or above	-0.143**	0.0170	-0.201***	-0.268***	-0.447***
Graduate program participant	0.254***	-0.116	0.0326	-0.145*	-0.261**
Central agency experience	0.556***	0.327***	0.215**	0.132	0.188
Controls					
Maternity leave	0	0	-4.458***	-3.978***	0
Time at level	0.0588***	0.142***	0.0926***	0.109***	0.122***
Time at level squared	-0.00163*	-0.00399***	-0.00167***	-0.00210***	-0.00238***
Age	-0.176***	-0.228***	-0.237***	-0.256***	-0.179***
Age squared	0.00177***	0.00226***	0.00232***	0.00269***	0.00187***
Year FEs	YES	YES	YES	YES	YES
Observations	91019	57972	96556	68969	23813
Pseudo R^2	0.031	0.033	0.039	0.042	0.047

Table 3 .21: Separation, 2002-2020 (Sample includes only those from NESB)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0489*	-0.0331	0.00406	0.00159	0.0795**
Disability	-0.228***	-0.176***	-0.177***	-0.0938*	0.0649
Born in Australia	0.484***	0.359***	0.293***	0.304***	0.323***
Indigenous	0.230***	0.355***	0.266***	0.181**	0.0986
Skills					
Accounting/Economics/Finance degree	-0.173***	-0.108*	-0.0534	0.0186	0.112**
Bachelor or above	0.197***	0.101***	-0.0532**	-0.210***	-0.301***
Graduate program participant	0.169***	-0.0405	0.0245	-0.109***	-0.277***
Central agency experience	0.299***	0.0722	0.0489	-0.0346	-0.0400
Controls					
Maternity leave	-4.542***	-4.574***	-5.103***	-4.388***	0
Time at level	0.0974***	0.169***	0.117***	0.100***	0.114***
Time at level squared	-0.00374***	-0.00511***	-0.00289***	-0.00176***	-0.00265***
Age	-0.122***	-0.177***	-0.185***	-0.195***	-0.134***
Age squared	0.00119***	0.00170***	0.00184***	0.00210***	0.00155***
Year FEs	YES	YES	YES	YES	YES
Observations	412108	264471	409475	328204	148445
Pseudo R^2	0.033	0.037	0.032	0.036	0.041

Table 3 .22: Separation, 2002-2020 (Sample includes Australian ESB and Asia-born NESBs)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	-0.0370	-0.0214	0.0300	-0.00302	0.0778**
Disability	-0.239***	-0.196***	-0.188***	-0.108**	0.0484
Born in Australia	0.303***	0.0750	0.166**	0.129*	0.193*
Indigenous	0.237***	0.356***	0.258***	0.180**	0.102
Skills					
Accounting/Economics/Finance degree	-0.187***	-0.0949	-0.0667	0.0126	0.114**
Bachelor or above	0.209***	0.112***	-0.0491**	-0.209***	-0.298***
Graduate program participant	0.151***	-0.0366	0.0286	-0.0914***	-0.272***
Central agency experience	0.283***	0.0555	0.0446	-0.0339	-0.0565
Controls					
Maternity leave	-4.528***	-4.554***	-5.485***	-4.629***	0
Time at level	0.0984***	0.167***	0.118***	0.102***	0.113***
Time at level squared	-0.00377***	-0.00506***	-0.00288***	-0.00184***	-0.00262***
Age	-0.119***	-0.171***	-0.176***	-0.192***	-0.128***
Age squared	0.00116***	0.00164***	0.00174***	0.00207***	0.00148***
Year FEs	YES	YES	YES	YES	YES
Observations	394905	252568	387325	313390	146028
Pseudo R^2	0.032	0.035	0.031	0.036	0.041

Table 3 .23: Separation, 2002-2020 (Sample includes Australian ESB and Europe-born NESBs)

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	0.178	-0.104	0.187	0.106	-0.125
Disabled	0.753**	0.473	0.651*	-0.584	0.404
NESB	-0.0193	0.282	-0.563*	-0.0609	-1.701
Indigenous	-0.422	0.169	-0.147	0.708	2.101***
Skills					
Accounting/Economics/Finance degree	-0.508	-0.232	-0.0640	0.267	1.068**
Bachelor or above	0.524**	0.382*	0.435**	0.298	-0.537
Graduate program participant	-2.010***	-1.338***	-0.606*	-0.303	-0.514
Central agency experience	1.282***	0.228	0.814***	0.298	0.663
Controls					
Maternity leave	-1.593	0	0	-1.275	0
Time at level	-0.456***	-0.208**	-0.292***	-0.189***	-0.104
Time at level squared	0.0131***	0.00334	0.00802***	0.00716***	0.00451*
Age	-0.00129	-0.0730	-0.00150	-0.0306	0.170
Age squared	-0.000285	0.000374	-0.0000994	0.000177	-0.00174
Year FEs	YES	YES	YES	YES	YES
Observations	82830	60389	97040	77986	34081
Pseudo R^2	0.127	0.065	0.058	0.039	0.087

Table 3 .24: Separation, baseline model, 2018-2020

Variable	APS4	APS5	APS6	EL1	EL2
Attributes					
Female	0.134	-0.152	0.141	0.0153	-0.202
Disabled	0.802**	0.547	0.748**	-0.585	0.408
NESB	0.00741	0.283	-0.528*	-0.0215	-1.619
Indigenous	-0.429	0.215	-0.147	0.655	2.128***
Skills					
Accounting/Economics/Finance degree	-0.413	-0.247	-0.113	0.298	1.209**
Bachelor or above	0.424*	0.363	0.408**	0.273	-0.665*
Graduate program participant	-1.956***	-1.211***	-0.605*	-0.275	-0.413
Central agency experience	0.910**	-0.201	0.534*	0.0665	0.540
Controls					
Maternity leave	-1.550	0	0	-1.284	0
Time at level	-0.429***	-0.206**	-0.279***	-0.190***	-0.0874
Time at level squared	0.0123***	0.00341	0.00782***	0.00742***	0.00371
Age	0.0304	-0.0439	0.0205	-0.00915	0.205
Age squared	-0.000609	0.000117	-0.000316	-0.0000227	-0.00207
Year FEs	YES	YES	YES	YES	YES
Job FEs	YES	YES	YES	YES	YES
Observations	82353	58398	87572	75708	26326
Pseudo R^2	0.139	0.088	0.067	0.051	0.103

Table 3 .25: Separation, model with job family fixed effects, 2018-2020

Appendix 3 .C Summary of APSED data cleaning routine

Overview: Section 44 of the Public Service Act 1999 gives the APSC the power to request information required for the presentation to Parliament of a report into the state of the (public) service. In pursuit of this goal, the APSC maintains the APS Employment Database, which tracks all employment movements in the Australian Public Service. Data are sourced from each department's corporate section.

The two (related) files provided by the APSC for analysis:

- Twentyyear, which is a file of all movements including demographic characteristics.
- Snapshots, which is derived from the Twentyyear file, is a combination of APS-wide censuses from 2001 to 2020 taken in December. June snapshots also exist, but have not been used in our analysis.

Using the twentyyear file, we extract values (where they exist) for each of the following:

- Sex (female = "W", male = "M")
- Bachelor or above (highestqualification = 1, 2, 3, or 4)
- Field of study (fos1 or fos2 = 2, 3, or 4 corresponds to accounting, economics or finance)
- Disability (disable = 11)
- Non-English speaking background (nesb = 1 or 2 for children of immigrants or immigrants)
- Graduate program (maxlevel = 60 or 65)
- Experience with a central agency (provided by APSC)

For ease of use, in most of the analysis, we treat these as time invariant and so there is one row for each individual linked with the unique panel id.

Using the twentyyear file, we recode the SAS date for birthday and then subtract arrival year (arrival) from birthday to define the age at which the employee enters Australia. A small number of individuals with missing values (or invalid dates) in arrival year or birthday are removed from the data.

Promotions are defined within the snapshot files where a person moves up a level as defined by the variable `maxlevel`, which is the substantive classification of a person's job. This avoids measuring as promotions people who are in interim or acting roles.

While there is a variable (`mvmt`) that records promotions, engagements and separation, it misses people moving through levels via broadbanding and thus undercounts promotion, mainly at lower levels. Broadbanding is the practice of having some jobs defined across multiple levels (e.g. APS5/APS6) and the individual moving from one category to the other without having to explicitly apply for promotion.

Separations: Using the variable `mvmt`, we define separation as those with values of 501, 502, 503, 504, 506 and 517. These codes correspond to different forms of voluntary resignation and termination. There are other reasons for leaving the public service, such as retirement due to age, death and invalidity which we do not define as separation. The values 505, 507, 508, 511, 514, 515, 516, 518, 519, 520, 521, 522 and 599 include these categories and other separations that are unlikely to be separation to another job outside the public service.

Time at level: The variable called `lal` – length at level - is measured in days. However when we link this to the snapshot file we need to recode the value for both the separation and promotion modelling because `lal` starts again when someone is promoted and so we create an extra row and add the lagged value of `lal` with the new value of `lal`. For example, if an individual has an `lal` value of 365 prior to promotion and a value of 65 in the year of promotion we add these together. Otherwise the value is close to a perfect predictor for promotion. The year of separation often has no value for `lal` since the person has left by the time of the census/snapshot. In this case we add one year for simplicity. Finally time at level is divided by 365 to express it in years.

`age` (and hence age-squared) is included in the snapshot file so does not require any data re-coding. We use the year which is recorded in the snapshot file (*snap*) to create the year fixed effects.

Appendix 3 .D Sensitivity Analysis to Missing Data

In the main analysis, we set 'diversity' indicators equal to zero when we are unable to determine if an individual is described by that characteristic. Female is never missing, but for 26.4 per cent of cases we are unable to determine if an individual is NESB, for 16.7 per cent of cases we are unable to determine if a person is Indigenous and for 26.1 per cent of cases we are unable to determine if an individual has a disability. We think that missing in these situations can be interpreted as not applying because people can skip over these questions when they complete the survey instrument.

To check whether this matters for our analysis, we re-estimated all of our models dropping the missing values (rather than setting them to zero) for NESB, Indigenous and Disability. Table 3 .26 shows these results for promotion for the baseline model for all years, 2002-2020. These results can be compared to Table 3 .8.

The main conclusions do not change when we drop missing values. Some coefficients increase and some decrease, but the patterns of sign and statistical significance are the same whether we include the missing values or exclude them. We do not present other results without missing values, but the conclusion is the same. These results can be obtained from the authors upon request.

	APS4	APS5	APS6	El1	EL2
Attributes					
Female	-0.136***	-0.150***	-0.221***	-0.155***	0.0516
Disabled	-0.213***	-0.253***	-0.308***	-0.332***	-0.147*
NESB	-0.147***	-0.0976***	-0.191***	-0.348***	-0.482***
Indigenous	-0.559***	-0.669***	-0.440***	-0.347***	-0.223
Skills					
AEF degree	-0.0463*	-0.0707***	0.171***	0.106***	0.184***
Bachelor or above	0.471***	0.494***	0.154***	0.0930***	-0.115***
Graduate program	0.116***	-0.232***	0.151***	-0.0144	0.157***
Central agency experience	0.585***	0.274***	0.444***	0.188***	0.548***
Controls					
Maternity leave	-0.515***	-0.483***	-0.341***	-0.290***	-0.746***
Time at level	-0.0795***	0.0712***	0.131***	0.145***	0.151***
Time at level squared	-0.000725**	-0.00656***	-0.00827***	-0.00725***	-0.00721***
Age	0.0961***	0.115***	0.200***	0.252***	0.294***
Age squared	-0.00131***	-0.00156***	-0.00252***	-0.00297***	-0.00324***
Year FEs	YES	YES	YES	YES	YES
Regression Information					
Observations	349880	249264	311688	211131	84258
Pseudo R^2	0.092	0.055	0.069	0.062	0.061

Table 3 .26: Promotion, Baseline model 2002-2020 with missing values removed

Appendix 3 .E Analysis split by gender

Separations by EEO group and gender

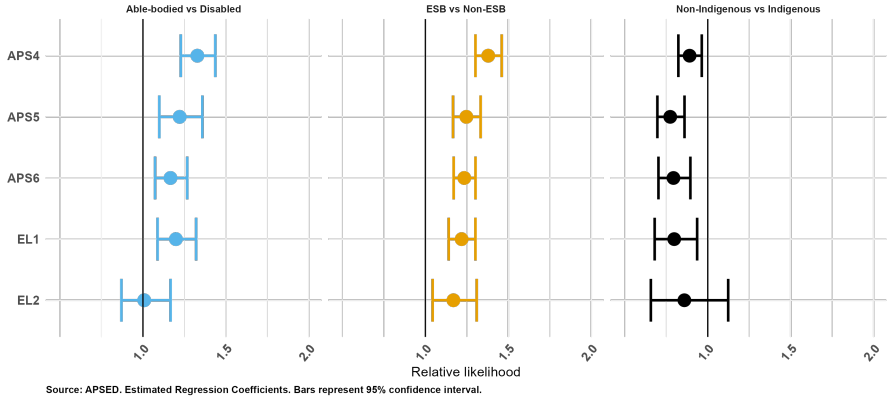

Figure 3 .18: Separations, females, by EEO group

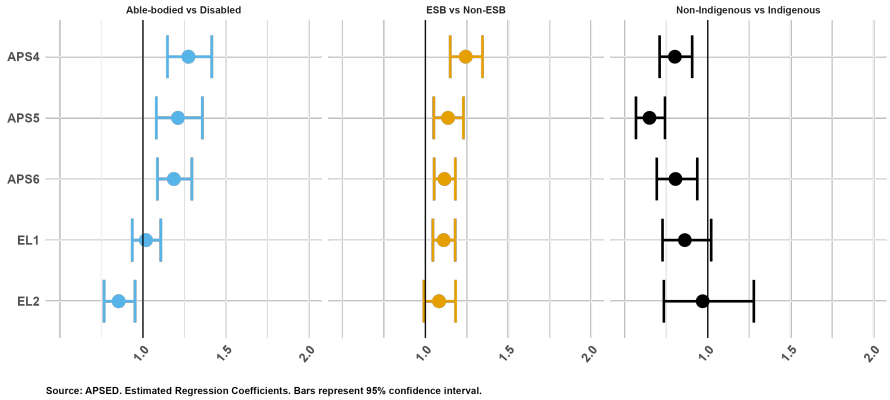

Figure 3 .19: Separations, males, by EEO group

Disaggregated NESB Promotions, by gender

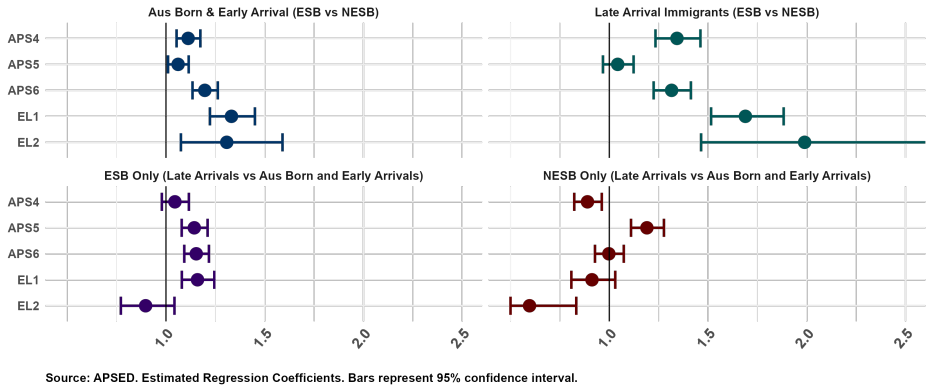

Figure 3 .20: Promotions, females, by arrival in Australia

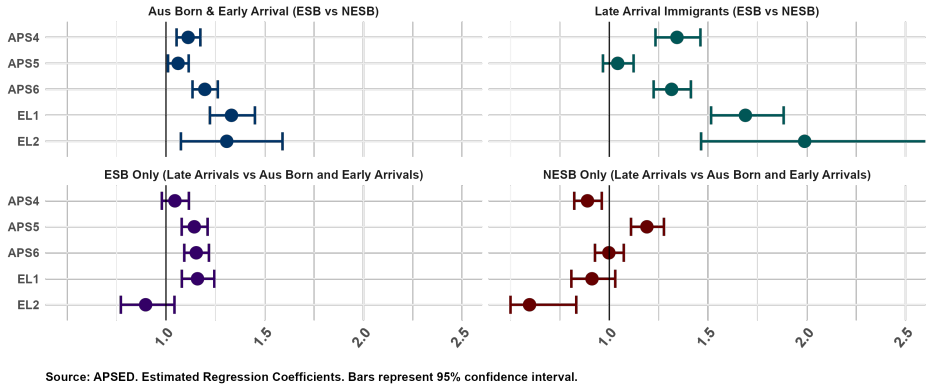

Figure 3 .21: Promotions, males, by arrival in Australia

Conclusion

This thesis demonstrates the transformative potential of linked administrative microdata in evaluating Australian government policies. As data sharing ecosystems mature, the capacity to answer previously intractable policy questions expands exponentially. Through three distinct Chapters, this research showcases how granular, unit-record data held by public sector agencies can be harnessed to assess the effectiveness of policies across tax, competition, and workforce equity policies.

The first Chapter provides the most comprehensive evaluation to date of Australia's business investment tax breaks (ITBs). It finds that ITBs implemented during the Global Financial Crisis significantly boosted investment, particularly among unincorporated businesses not subject to dividend imputation. In contrast, ITBs introduced during the COVID-19 pandemic and in normal economic times had limited impact. These findings highlight the importance of macroeconomic context and policy design, suggesting that ITBs are most effective during credit supply shocks and for firms facing financing constraints.

The second Chapter fills a critical gap in Australia's competition policy landscape by constructing the first M&A database using administrative data. It reveals that around 1,500 mergers occur annually, with large firms disproportionately acting as acquirers and less productive firms more likely to be targets. The chapter also identifies serial acquisition patterns in sectors, offering timely insights ahead of Australia's shift to a mandatory merger notification regime in 2026.

The third Chapter examines promotion and retention outcomes in the Australian Public Service (APS), uncovering persistent inequities. While women's promotion prospects have improved markedly—especially at senior levels—staff from non-English speaking backgrounds (NESB), Indigenous Australians, and people with disabilities continue to face significant barriers. Notably, the promotion penalty for NESB staff persists even among those born in Australia or who arrived at a young age, suggesting that language fluency and cultural assimilation alone do not explain the disparity. These findings informed the APS's first employment strategy for culturally and linguistically diverse staff and contributed to the development of Senior Executive targets implemented in April 2024.

Together, these chapters reveal that policy effectiveness in many circumstances depends strongly on individual- or firm-level characteristics, underscoring the importance for policy evaluation of Australia's large investment in linked microdata assets in recent years.