Impacts on Workers from the Shutdown of a National Automotive Manufacturing Industry

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Abstract

Australia's 100-year-old automobile industry ended in 2017 with the closure of the Ford, General Motors, and Toyota assembly plants. We study how this major economic event affected the industry's core blue-collar workforce economically and mentally. Using a difference-in-differences approach, we find that the economic wellbeing of automotive industry workers – as measured by employment, welfare use, earnings, and occupation stability – worsened in the years following plant closure announcements and closures. These effects were most pronounced and persistent for older lower skilled workers, with estimates indicating a 12 percentage point drop in employment, a 5 percentage point increase in unemployment related welfare use, a 44% decline in salary income, and a 19 percentage point increase in occupation change. In contrast to these economic effects, we do not find evidence for worsening mental health outcomes measured by medication and therapy use. A possible explanation is that the support systems initiated by industry and government, such as counselling, resilience training, and wellbeing programs, effectively supported workers' mental wellbeing. It could also be the case that the entire industry closure had less of a stigmatising effect on laid-off workers, as opposed to specific firm closures.

Keywords: Automobile industry closure; Blue-collar workforce; Economic wellbeing; Mental health; Difference-in-differences

JEL classification: L62; I10; I14; J63

1 Introduction

Economic uncertainty is increasingly threatening entire industries within countries, driven by technological advancements (Acemoglu and Restrepo, 2019), global competition (Cooke et al., 2019; Grossman and Oberfield, 2022), and climate change policies (Dupuis et al., 2024). As automation and production shifts to lower-cost countries, industries like automotive manufacturing, textiles, and coal mining are at risk of rapid decline, particularly in countries with higher labour costs and stricter regulations. These large-scale industry closures can lead to significant workforce disruptions, heightening economic insecurity and mental health challenges for displaced workers.

In this paper, we leverage a unique natural experiment in Australia, where the entire car manufacturing industry shut down between 2016 and 2017. Major manufacturers Ford, General Motors (GM), and Toyota announced their exit from Australian manufacturing in 2013 and 2014, leading to the closure of all domestic car production by 2017. This event provides an ideal setting to study the impacts of industry-wide job displacement, as approximately 14,000 workers, many blue-collar with limited formal education, were affected (Productivity Commission, 2014; Wallis & ACIL Allen, 2020).

Impacts on workers from an industry shutdown may differ from those for a single plant closure due to several reasons. On the one hand, the extreme media and political attention associated with a whole-of-industry closure can prompt generous redundancy packages, government support for retraining and relocation, and health and wellbeing programs, leading to relatively smaller impacts.[1] On the other hand, impacts can be expected to be larger, given fewer (or no) comparable employers for redundant workers to transition to, training required for occupation change, weakened local labour markets, and relocation costs (Cederlöf, 2024; Productivity Commission, 2014; Rud et al., 2024). The magnitude of such adverse effects is generally greater for older, lower educated, lower skilled, and high-tenure employees (Carrington and Fallick, 2017; Quintini and Venn, 2013), who accounted for a large share of Australia's automotive manufacturing workforce. Such workers often experience greater difficulty (and lower net benefit) in retraining (Braxton and Taska, 2023; Jacobson et al., 1993), in transferring accumulated industry-specific skills elsewhere (Productivity Commission, 2014; Rud et al., 2024), and in returning to work after long spells of unemployment due to human capital losses (Haynes et al., 2011). We would also expect negative economic effects to flow onto worse mental health, due to factors such as social exclusion caused by reduced participation in economic activities (McLachlan et al., 2013), increased stress, and lower self-esteem (Wilson and Finch, 2021).

We study how Australia's car industry closure affected the industry's core blue-collar workforce economically and mentally, using linked administrative tax, welfare, and healthcare

[1]Recent evidence focusing on mass GM factory layoffs in the US and Canada shows that media coverage shapes public perceptions of accountability and policy responses with notable shifts documented in support for trade policy (Brutger and Guisinger, 2024).

records and a Difference-in-Differences (DiD) event study design, over the 2010-2022 period. The rich administrative data allow us to construct a longitudinal dataset tracking more than 4,000 displaced automotive manufacturing workers in years before and after being made redundant. We estimate the impact of the average automotive industry worker's job loss on labour market outcomes and mental healthcare use, employing a panel data model with time and individual fixed effects. This estimator compares the evolution of outcomes of displaced workers relative to a group of observationally similar unaffected workers. We construct the control group by matching blue-collar automotive industry workers to similar blue-collar workers in other non-automotive manufacturing or construction industries working in the same occupations and residing in similar regions. We also consider variations to the definition of our treatment and control groups and to the matching procedure and show that our results remain robust and quantitatively similar.

We find that the economic wellbeing of blue-collar automotive industry workers worsened in the years following car plant closure announcements and actual closures, in comparison to never-treated workers with the same occupations working in non-automotive manufacturing or construction industries. In particular, in the year following the closures, automotive industry workers experienced a 6 percentage point lower chance of being employed, a 4 percentage point increase in welfare use, a 29% drop in salary income, and a 15 percentage point increase in occupation change. These effects largely persisted for the next five years. Heterogeneity analysis by skill level and age shows that effects were more pronounced among lower skilled older workers, with younger higher skilled workers being the least affected.

In contrast to sizable economic impacts, we find no evidence of worsening mental health outcomes in terms of psychological therapy service and mental health medication use. We attribute this surprising finding to the comprehensive and well-targeted support systems in place for redundant workers, implemented well in advance of the automotive plant closures and continued in the post-closure period. Our results might also reflect relatively lower levels of job loss-related stigma originating from an entire industry closure, as opposed to layoffs associated with specific firm closures (Green, 2011).

Our findings contribute to the understanding of the economic and mental health impacts of large-scale job loss – particularly those arising from an entire industry closure – which have received less attention compared to specific firm closures, despite high contemporary relevance. Mining industries are the notable exception, where prior studies have documented significant and persistent reductions in hourly wages and earnings of displaced miners (Rud et al., 2024) and negative flow-on effects onto women in manufacturing employment (Aragón et al., 2018) following the UK coal mine industry closure. A few studies have also used modelling techniques to estimate labour market impacts of the phasing out of coal in future years in different settings (Clark and Zhang, 2022; Feng et al., 2023; Heinisch et al., 2021). This existing literature has mainly focused on the overall labour market impacts of the coal industry closure and the heterogeneity of impacts by individual characteristics such as age, occupation type, and location. However, less attention has been given to health impacts. Moreover, to our knowledge, there are no studies examining effects of entire manufacturing industry closures.[2] By exploring a range of economic as well as mental health impacts, this study provides new insights into how workers can be affected when a whole important manufacturing industry closes.[3]

In addition to advancing the literature on the economic and mental health impacts of a manufacturing industry shutdown, this study contributes to several broader fields. First, it adds to research on effects of mass layoffs by showing how an industry-wide closure affects a range of economic outcomes, building on a large well-established literature documenting negative effects on displaced male blue-collar workers in terms of life-time earnings losses, labour force participation, migration, and loss of specific human capital (Bertheau et al., 2023; Couch and Placzek, 2010; Cuccu and Royuela, 2024; Davis and Von Wachter, 2011; Hijzen et al., 2010; Jacobson et al., 1993; Stevens, 1997). Second, it is related to a subset of studies which document negative mental health effects on workers affected by selected car plant closures in the United States (US) (Dufault et al., 2022; Eisen et al., 2020; Hamilton et al., 1990; Venkataramani et al., 2020) and by involuntary unemployment more generally (Blasco et al., 2024; Browning and Heinesen, 2012; Bubonya et al., 2017; Kassenboehmer and Haisken-DeNew, 2009; Kuhn et al., 2009; Marcus, 2013; Reichert and Tauchmann, 2017). Lastly, it offers insights into the adequacy of provisions during mass redundancies (Britto et al., 2022; Classen and Dunn, 2012), highlighting the importance of holistic support extending beyond job and career assistance to health and wellbeing provision, in minimising adverse impacts on affected workers.

The rest of the paper is organised as follows. Section 2 provides background on the automotive plant closures and support programs initiated by industry and government for affected workers. Section 3 describes the data, sample, and outcome measures. Section 4 details the empirical approach. The results are presented and discussed in Section 5. Section 6 concludes.

2 Automotive industry closure and support for workers

2.1 Plant closures

The closure of Australia's car manufacturing industry was a result of multiple factors including an overvalued Australian dollar, a consumer shift to smaller foreign cars, Australia's high production and wage costs, and government cuts to the industry's taxpayer subsidies

[2]Charles et al. (2019) explore the link between the general decline in manufacturing employment and labor market outcomes among prime-age Americans since 2000.

[3]Although the downfall of Australia's automotive assembly industry attracted wide media attention and discussions in policy circles, robust research investigating the causal impact of job loss on economic and health outcomes of affected workers is limited. There have been several qualitative studies exploring worker outcomes in the months following car plant closures (Anaf et al., 2013; Irving et al., 2022; Wallis & ACIL Allen, 2020).

(Spinks, 2014; Toscano, 2019). Five plants belonging to the three main car manufacturers shut down, effectively ending a 100-year long industry.[4] Plans to close the manufacturing facilities were publicly announced by the car companies between mid-2013 and early 2014, with final closures occurring in late 2016 and 2017. Four plants were located in adjoining regions in the state of Victoria and one plant in the state of South Australia. Four of the five plants gradually scaled back production, allowing for the early departure of workers to take up other employment opportunities, while the other plant maintained full production levels and its workforce until full closure.[5] The closure announcement and closure dates of the different car plants are summarised in Appendix Table .A.1.

Along with the main car manufacturers, several associated suppliers in the automotive supply chain were also affected. Estimates indicate that approximately 26 of the 140 automotive supply chain companies in Victoria and around 20 of the 75 companies in South Australia closed, with many others having started diversifying into other industry sectors (Wallis & ACIL Allen, 2020).[6] Approximately 14,000 employees from the car companies and associated local suppliers lost their jobs in total. The affected workforce included a relatively high proportion of middle and older aged high-tenure blue-collar workers with low levels of formal education and skills training (Productivity Commission, 2014; Wallis & ACIL Allen, 2020).

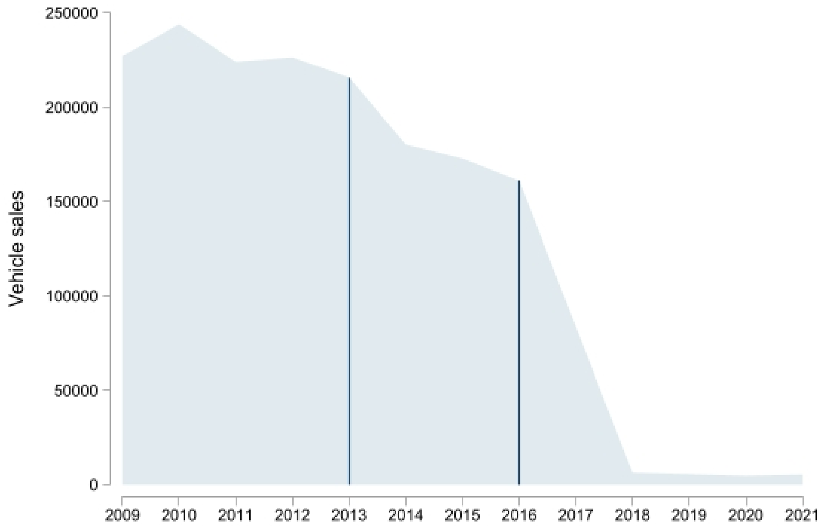
Figure 1 illustrates the gradual downfall of Australia's automotive manufacturing industry, measured by the production of motor vehicles. After a drop of sales in 2009 following the Global Financial Crisis, production picks up marginally, before experiencing a continuous fall from 2010 onward. A significant drop is seen post-2013 soon after automotive plant closure announcements were made, followed by a sharp decline post-2016 when the plants ceased operations. Following final closures in 2017, the number of vehicles produced in the ensuing period is negligible.

[4]These closures followed a well-established pattern of exits by key automobile producers, with Chrysler and Nissan ceasing production in 1989 and the late 1990s, respectively, and Mitsubishi closing plants in 2004 and 2008 (Beer, 2018).

[5]Research and design activities continued in most of these plants despite the closure of the automotive assembly industry. Ford Australia continues to employ around 1,000 employees in its research, design, and engineering facilities across its operations in Victoria (Collie, 2023), while around 165 engineering staff were retained at Toyota under plans for a Centre of Excellence with a design and engineering capability for international models (Department of Industry, Innovation and Science, 2020).

[6]While many of the larger Tier 1 and Tier 2 suppliers who provided parts directly and indirectly for car manufacturing were contractually committed to continue production until car plant closures, Tier 3 suppliers providing raw materials had greater flexibility in diversifying into other sectors before the plant closures.

Figure 1: Motor vehicle production in Australia, 2009-2021



Source: International Organisation of Motor Vehicle Manufacturers, sourced from CEIC, 2021, available at https://insights.ceicdata.com/Untitled-insight/views.

2.2 Government and industry support

In response to the end of car manufacturing in Australia, the federal and state governments of Victoria and South Australia, together with the car companies and unions, implemented various programs designed to ease the impacts on affected workers in the car companies and supply chain industries. Many of these programs were put in place up to three years prior to the actual closure of the plants, following the early notifications of closures. Total support amounted to approximately $380 million (Wallis & ACIL Allen, 2020), and centered around delivering career planning and job search support as well as health and wellbeing support. In what follows is a summary of the different types of support provided. See Appendix Table .A.2 and Wallis & ACIL Allen (2020) for more specific details.

In collaboration with the Department of Industry, Innovation and Science, the state governments and car manufacturers offered a variety of career planning and job support services, including extensive pre-retrenchment training, funding for cost of training linked to a Career Transition Plan, access to personalised career management advice, and financial support for further education. Each of the automobile manufacturers also offered substantial redundancy payments to workers. Payments ranged between $80,000–$96,500 for non-trade production and production-line workers to between $100,000–$117,555 for skilled trade workers, and consisted of sick pay, annual leave, and long service leave entitlements, and four weeks' pay and additional "loyalty" bonus payments for each year of service (Dowling, 2014; McDonald, 2013; Michael, 2014).[7] Along with redundancy packages, a range of financial advisory services were offered – both prior to and post-closure – targeted at helping workers make decisions on how

[7] At plants where terminations occurred in phases, workers received a pro-rata redundancy payment if they left prior to the closures.

best to use their redundancy payments.

Health and wellbeing support primarily focused on mental health, resilience training, and post-closure services, provided both on-site and through offsite providers and government and community-based facilities. Workers were provided with gym facilities, mental health related workshops focusing on knowledge and tools to support themselves and others during the transition period, and free access to professional counselling to discuss personal, financial, or work-related issues. Resilience training was offered to workers and their families through both formal and informal channels such as schools or sporting clubs. Workers also benefitted from the continuation of services provided post-closure through transition and outreach centers, which remained open for up to 26 months after closures. In addition to providing ongoing services and support in terms of job search, these centers served as a place for workers to continue to engage with their former colleagues and interact socially.

3 Data and sample

3.1 Data

We use administrative data from the Person Level Integrated Data Asset (PLIDA) released by the Australian Bureau of Statistics (ABS), for the years 2010/2011 – 2022/23. PLIDA is a partnership among Australian Government agencies to combine information on population demographics (from the Census), employment and occupation (from the Census and Australian Taxation Office [ATO]), income and wages (from the ATO), education (from the Department of Education), welfare payments (from the Department of Social Services), and healthcare use (from the Department of Health), to create a comprehensive picture of the ever-resident population of Australia overtime (ABS, nd). The datasets are linked through a 'person linkage spine', covering all people who were resident in Australia at any point during a given reference period, based on the combined population from the Medicare Consumer Directory, DOMINO Centrelink Administrative Data, and Personal Income Tax (*Ibid*).

The PLIDA data is well suited for our analysis because its very large sample size, geographic identifiers, and detailed occupation and industry codes allow us to identify precise treatment and control groups. The combined information from multiple datasets also allow investigation of effects on a wide range of economic and health outcomes. Moreover, its span of 2010-2022 allows us to examine pre-treatment trends and test the validity of our identification approaches, as well as to explore the persistence of effects several years after the industry closure.

3.2 Sample restrictions

Our focus is on exploring the impacts of the automotive industry closure on substantively employed, blue-collar, working-age individuals.[8] To do so, we retain individuals using restrictions based on characteristics measured in 2011, which is the year the Census was conducted. Specifically, we restrict the sample to blue-collar employees, consisting of technicians and trade workers (relatively higher skilled) and machinery operators and drivers and labourers (relatively lower skilled). We consider workers aged 24-55 in 2011 working at least 25 hours per week (reported in the 2011 Census), who in the 2010-2011 financial year had a gross salary income consistent with a substantive job (greater than AUD 27,355, the minimum annual earnings for the period July 2010-June 2011).[9] These restrictions leave us with a sample of 962,390 individuals.

We further restrict the sample to people working in three main industry groups in 2010/11 (reported in the 2011 Census): transport equipment manufacturing (henceforth referred as to as automotive manufacturing), other manufacturing industries (excluding automotive manufacturing and automobile supply chain subindustries), and construction.[10] The first group consists of the treatment group employed in automotive assembly plants. The second and third groups form the control industries. The choice of our comparison group is motivated by three main reasons. First, blue-collar occupations in other manufacturing industries and construction are likely involved in manual labour like car manufacturing, meaning that workers are likely to be similar in terms of socioeconomic characteristics and skill levels. Second, the construction industry is a relatively stable industry not reliant on a few major employers, and the construction and other manufacturing industries were not subject to major economic shocks similar to the automotive manufacturing industry during the study period. Third, it is unlikely that other manufacturing and construction workers were affected by the closure of the automotive manufacturing industry, given minimal linkages between the industries.[11] Our sample includes 365,393 individuals after imposing the industry restrictions.

Although we limit the sample to blue-collar workers, there are large differences in the types of occupations of workers in the treatment and control groups, which suggests that the skill compositions of the two groups are somewhat different. To enable the comparison of tightly defined treatment and control groups, we match treatment and control observations with the same (exact) four-digit occupation code in 2010/11, thereby ensuring that all treatment

[8] Blue-collar workers accounted for 64% of the automotive manufacturing workforce in 2011 (Productivity Commission, 2014). We omit community and personal service workers, clerical and administrative workers, and sales workers whose occupations are not very relevant to automotive manufacturing. We also omit managers and professionals whose roles are less dependent on job-specific knowledge, and hence are less likely to be affected by the industry closure.

[9] The minimum weekly wage for 2010/11 was AUD 569.90. We multiply this by 48 to derive the annual minimum wage of AUD 27,355.

[10] The specific industries considered under each experimental group, and the automobile supply chain subindustries omitted from other manufacturing industries, are listed in Appendix Table .B.1.

[11] To test the robustness of this last assumption, we also consider an alternative control group of workers residing in a different state. These workers were unlikely to be affected by the closure of the automotive manufacturing industry.

observations have a control with the same occupation.[12] Specifically, we compare treated workers who are product assemblers, forklift drivers, and electricians, for example, with control workers with the same occupations. Appendix Table .B.2 lists the most frequent four-digit occupations among the treatment sample, for whom we find matched workers engaged in the same occupations from the control group. This approach enables matching each group more precisely on knowledge and skills in terms of occupations but comes at the expense of losing observations in each group for which there are no matching occupations in the other group.[13] We test the robustness of our estimates to a less restrictive propensity score matching method.

In our final sample restriction, we focus on people residing in specific local labour markets to define our treatment and control groups.[14] Our treatment group consists of workers who reside in the five labour market regions in which the automotive manufacturing plants were based. Our control group focuses on workers residing in major city and inner-regional labour markets in the same two states, excluding regions in which the car plants were located and those contiguous to them. We exclude the automotive plant and adjoining regions to account for any possible local spillovers that could occur – for instance if redundant automotive manufacturing workers were to transition into other manufacturing sectors or the construction industry. We focus on the same states in which automotive plants were located to control for similar trends in state-level industrial policies. We test the sensitivity of our results to considering control industry workers attached to local labour markets in a different state. Our final dataset contains 8,230 individuals, consisting of 4,115 workers each in the treatment and control industries.

3.3 Outcome variables

We explore a range of economic and health outcomes for workers. The economic outcomes include employment status (employee and self-employed), salary income, occupation instability, unemployment benefit use, and disability pension use (see Table 1 for definitions). We expect that the plant closures led to significant decreases in employment and salary income, especially for older and less skilled workers. We explore occupation instability because workers in our sample are especially likely to experience changes to their occupations given the complete closure of the industry. Prior studies show that occupation switching plays a key role in the persistent decline in earnings following job loss (Huckfeldt, 2022; Kambourov and Manovskii, 2009; Stevens, 1997).

[12] The matching result is produced by randomly dropping observations such that there is an equal number of treated and control individuals in each matched stratum (occupation group).We do not match based on occupations in all pre-treatment years to avoid making the two groups artificially similar.

[13] Exact matching on occupation drops 1,576 individuals from the treatment group and 33,124 individuals from the control group.

[14] We define local labour markets using the largest sub-State regions in the Main Structure of the Australian Statistical Geography Standard, known as Statistical Area Level 4 (SA4) regions. SA4 regions have populations ranging from 100,000–500,000 persons and are designed to represent labour markets (ABS, 2021). Entire SA4s aggregate to Greater Capital City Statistical Areas and State and Territory. There are 108 SA4 regions covering the whole of Australia without gaps or overlaps (*Ibid*).

Working age Australians who are unable to find employment (above their reservation wage) will often rely on two welfare schemes. Unemployment benefits provide ongoing financial assistance to unemployed individuals who are actively seeking employment.[15] The Disability Support Pension (DSP) provides financial assistance for individuals suffering from a permanent physical, intellectual, or psychiatric condition that prevents them from working. Evidence suggests that unemployment and disability benefit recipients generally increase during economic downturns (Australian Institute of Health and Welfare, 2023; Moffitt, 2013; Mueller et al., 2016).

Focusing on mental health effects is also important, given possible flow-on effects from job loss onto health. For instance, people who experience long-term joblessness are at a greater risk of social exclusion due to reduced participation in educational, work-related, and community activities (McLachlan et al., 2013). Long-term job losses and negative income shocks can also increase stress and lower self-esteem (Wilson and Finch, 2021), particularly among men and blue-collar workers (Paul and Moser, 2009). We measure mental health effects based on healthcare use data from the Medicare Benefits Schedule (MBS) and the Pharmaceutical Benefits Scheme (PBS). The MBS contains information on the use of psychological services through the national public system (Medicare), while the PBS provides information on mental health-related drug prescriptions based on the Anatomical Therapeutic Chemical (ATC) Classification System. A potential limitation of these outcomes is that they do not directly measure mental health, but health seeking behaviour, as we only observe healthcare use rather than actual health outcomes. We are also unable to measure employer-provided healthcare which is not captured in our data.

[15] Newstart Allowance was an income support payment in place until March 2020, which was then replaced with JobSeeker Payment.

Table 1: Outcome measures

Variable	Definition	PLIDA source
Employment	Dummy=1 if earning a positive salary income	Personal income tax (ATO): 2010/11-2021/22
Log salary income	Log of nominal value deflated by the CPI	
Positive business income	Dummy=1 if earning any positive business income	
Occupation change	Dummy=1 if 2-digit occupation code changed each year relative to 2010/11*	
Welfare use	Dummy=1 if recipient of Newstart Allowance/ JobSeeker Payment or DSP	Data Over Multiple Individual Occurrences (DOMINO) (Dept of Social Services): 2010/11-2021/22
Psychological therapy service use	Dummy=1 if any annual use of psychological services through Medicare	MBS (Dept of Health): 2011/12-2022/23
Mental health medication use	Dummy=1 if any annual use of antidepressants, anxiolytics, or sedatives	PBS (Dept of Health): 2011/12-2022/23

* We note some limitations with our occupation change measure. Recent research finds that occupation change is under-reported in the ATO's tax return records, with it being less than half of that in the nationally representative and widely used Household, Income and Labour Dynamics of Australia (HILDA) survey (Hathorne and Breunig, 2022). The authors attribute this finding to limited incentives for individuals to update the occupation field on their tax return when they change occupations, since tax liabilities do not depend on occupation. They note that analysis that relies on changes over time – as in our case – may be influenced by biases in which types of occupational changes are captured and which are not. However, to the extent that any under-reporting of occupation change by treatment and control workers follows a similar trend, these biases will get differenced out, and the measurement error in this indicator is likely to be minimal.

3.4 Descriptive statistics

Table 2 shows sample means of selected indicators for machinery operators and drivers and labourers (henceforth referred to as lower skilled workers) and technicians and trade workers (henceforth referred to as higher skilled workers) in the treatment and control industries in 2010/11, the first year of our sample. Panel A indicates that age, marital status, and gender composition are similar across treatment and control industry workers of both skill levels, although there is a somewhat higher share of lower skilled males in our treatment group. The education and employment indicators within each skill level are also near equal among treatment and control workers, with generally higher education and salary levels for higher skilled workers as might be expected (panel B). The share of workers on welfare support is also comparable among the groups, despite a slightly higher share of lower skilled control industry workers compared to their treatment industry counterparts. Panel C indicates small differences in mental healthcare use, with somewhat higher usage among lower skilled control industry workers. Overall, the treatment and control workers within each skill level are largely comparable.

Table 2: Sample means in 2010/11

	Lower skilled workers		Higher skilled workers	
	Treatment	Control	Treatment	Control
A: Demographic variables				
Age	41.50	42.06	40.50	39.03
Married	0.739	0.708	0.748	0.752
Male	0.845	0.733	0.976	0.982
B: Education and employment				
Years of education	11.30	11.31	13.08	13.45
Log salary income	10.96	10.82	11.12	11.11
Positive business income	0.026	0.022	0.034	0.033
Welfare use	0.007	0.016	0.006	0.008
C: Mental healthcare use				
Psychological therapy service use	0.017	0.026	0.017	0.020
Mental health medication use	0.042	0.067	0.039	0.034
Observations	2,684	2,684	1,431	1,431

Notes: Lower skilled refers to machinery operators and drivers and labourers and higher skilled refers to technicians and trade workers. Treatment refers to treated workers in the automotive manufacturing industry. Control refers to similar unaffected workers employed in the non-automotive manufacturing and construction industries.

4 Empirical approach

We estimate the economic and health impacts of the automotive manufacturing closure using a DiD event study specification in which we compare changes in outcomes over time between automotive manufacturing workers and similar workers in other manufacturing sub-industries and in construction industries. This approach is represented by:

$$Y_{it} = \sum_{t=1}^{k} \alpha(period_t * treat_i) + \gamma_i + \gamma_t + \epsilon_{it} \tag{1}$$

where Y_{it} is the economic or health outcome of individual i in year t. The variable $(period_t * treat_i)$ denotes a series of event-time dummies (k) from 2011/12–2022/23, which are year dummies interacted with the treatment group indicator, equaling one for automotive manufacturing industry workers and zero for workers in the control industries. Each interacted coefficient is then compared to 2010/11, the base year of our sample. γ_i denotes individual fixed effects which control for unobservable time-invariant differences across individuals, potentially affecting economic and health outcomes. γ_t denotes year fixed effects which account for factors specific to a given year, such as nationwide policy changes which equally affect economic and health outcomes across locations. Standard errors are clustered at the individual level.

The specific yearly post-treatment indicators account for the fuzzy nature of the exact timing of treatment, given the ongoing impacts experienced before definitive closures. We might expect some effects to begin in the announcement period (2013/14), most likely for higher skilled workers with good alternative job options who leave voluntarily. However, most of the effects are likely to start when workers are retrenched, which for most is in 2016/17. It is important to note that the impacts we measure are an intention-to-treat. Most car companies and associated supply chain firms closed or diversified into other businesses following the industry closure. While some local suppliers could have transitioned into other industries before the automotive industry shutdown, we expect that most workers were 'treated' in terms of losing their jobs.

Our key identifying assumptions are that: (1) in the absence of treatment (car plant closure announcements and closures) the average economic and health outcomes of workers engaged in the automotive manufacturing and control industries followed the same trend; and (2) treatment had no causal effect before its implementation (no anticipation). While these assumptions cannot be guaranteed, our design allows us to test for this. The summary statistics which show that the two groups of workers are similar across many characteristics, and our matching approach which ensures comparison of workers with similar occupation-specific knowledge and skills, lend some support to our identification assumptions. Appendix Table .C.1 shows F-statistics and corresponding p-values for F-tests of joint significance of pre-trend coefficients across the 2011/12–2013/14 (pre-treatment) period. For most outcomes there is no significant pre-trend, where the null hypothesis of a zero effect cannot be rejected.

Recent DiD literature nevertheless cautions against the over-reliance on the statistical significance of pre-trends tests alone, due to several reasons (Kahn-Lang and Lang, 2020; Roth, 2022; Roth et al., 2023). First, there are problems of low power, where the inability to reject zero pre-trends could also mean an inability to reject pre-trends that under smooth extrapolations to the post-treatment period would produce substantial bias. Second, selection bias can arise from only analysing cases with an insignificant pre-trend (even if pre-trends are exactly parallel, this may not guarantee that the post-treatment parallel trends assumption is satisfied). Third, even if a significant difference in pre-trends is detected, one might still be interested in a treatment effect, especially if the post-treatment coefficients are substantially larger in magnitude compared to the pre-trend coefficients.

Rambachan and Roth (2023) suggest an alternative approach, where instead of requiring that parallel trends holds exactly, one can impose restrictions on how different the post-treatment violations of parallel trends can be from the pre-trends. This approach also allows for sensitivity analysis by constructing robust confidence intervals under restrictions on the possible violations of parallel trends. We follow this method and show that our results are robust.

5 Results

5.1 Economic outcomes

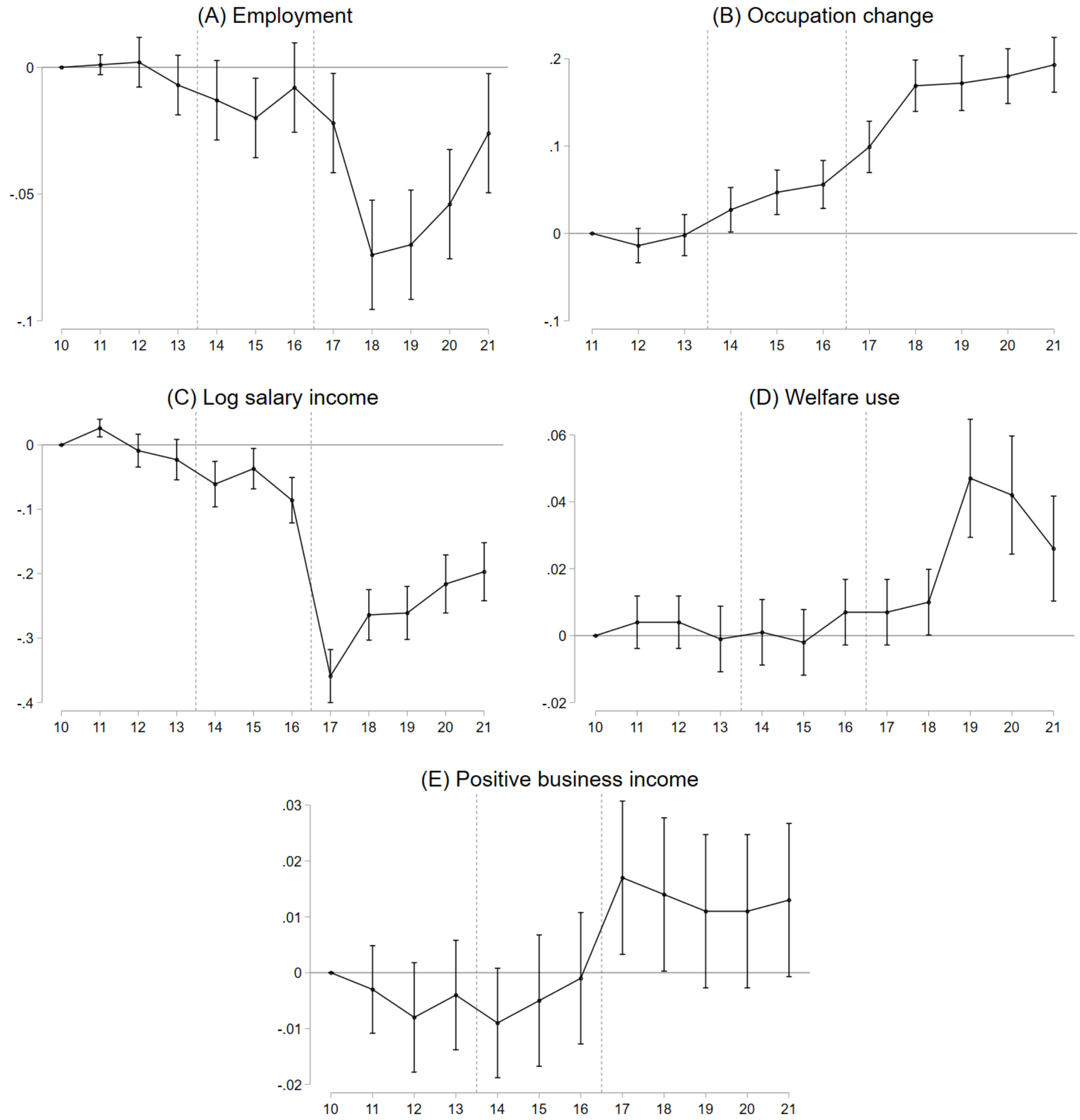
Panels A–E in Figures 2 and 3 present coefficient plots of estimates for the economic outcomes, for lower skilled and higher skilled workers, respectively.[16] The vertical dashed lines indicate when the plant closure announcements were made and when plant operations started ceasing. First focusing on Figure 2, we observe small effects during the post-announcement (pre-closure) period. A small proportion of low skilled workers left employment during this period (see A) – perhaps enticed by the redundancy package. A larger percentage seem to have taken on new jobs (see B), with these jobs being slightly lower paid (see C). They may have chosen this option in order to secure longer-term employment, at the cost of a little lost income.

Relative to the post-announcement period, a much larger group of workers left the labour market post-closure (see A). In 2018, for instance, employment of lower skilled automotive industry workers was 7.4 percentage points below that of their control industry counterparts, and these effects persisted for a number of years, though getting smaller with time. Many, but not all, also transitioned into welfare use (see D). A smaller, but not trivial proportion transitioned into self-employment, as evident from an increase in the share of business income earners (see E). Many workers moved into new jobs, some of which were in the same occupation, but a different industry. However, some required an occupation change (see B), which is likely higher in our context, given that workers couldn't transition to a similar plant in the same industry (i.e. move to another automotive manufacturer). Notably, the quality of jobs found – in terms of earnings – was significantly lower than the prior jobs: in 2017/18, earnings of lower skilled automotive industry workers were almost 40% lower compared to 2010/11 (see C). The effects seem to be permanent, remaining at a negative 20% five years later. This may be because these workers needed to move to new occupations, where their expertise, experience, or relevant skill level, was lower. It is also possible that this drop was caused by lower hours worked (rather than lower dollars earned per hour). Unfortunately, we cannot distinguish between these explanations given the unavailability of data on hours worked.[17]

[16] Regression estimates for the full sample and by skill level are reported in Appendix Table .D.1.

[17] Workers may have also transitioned into training programs (e.g., vocational education and training or university).

Figure 2: Estimated effects on economic outcomes for lower skilled workers

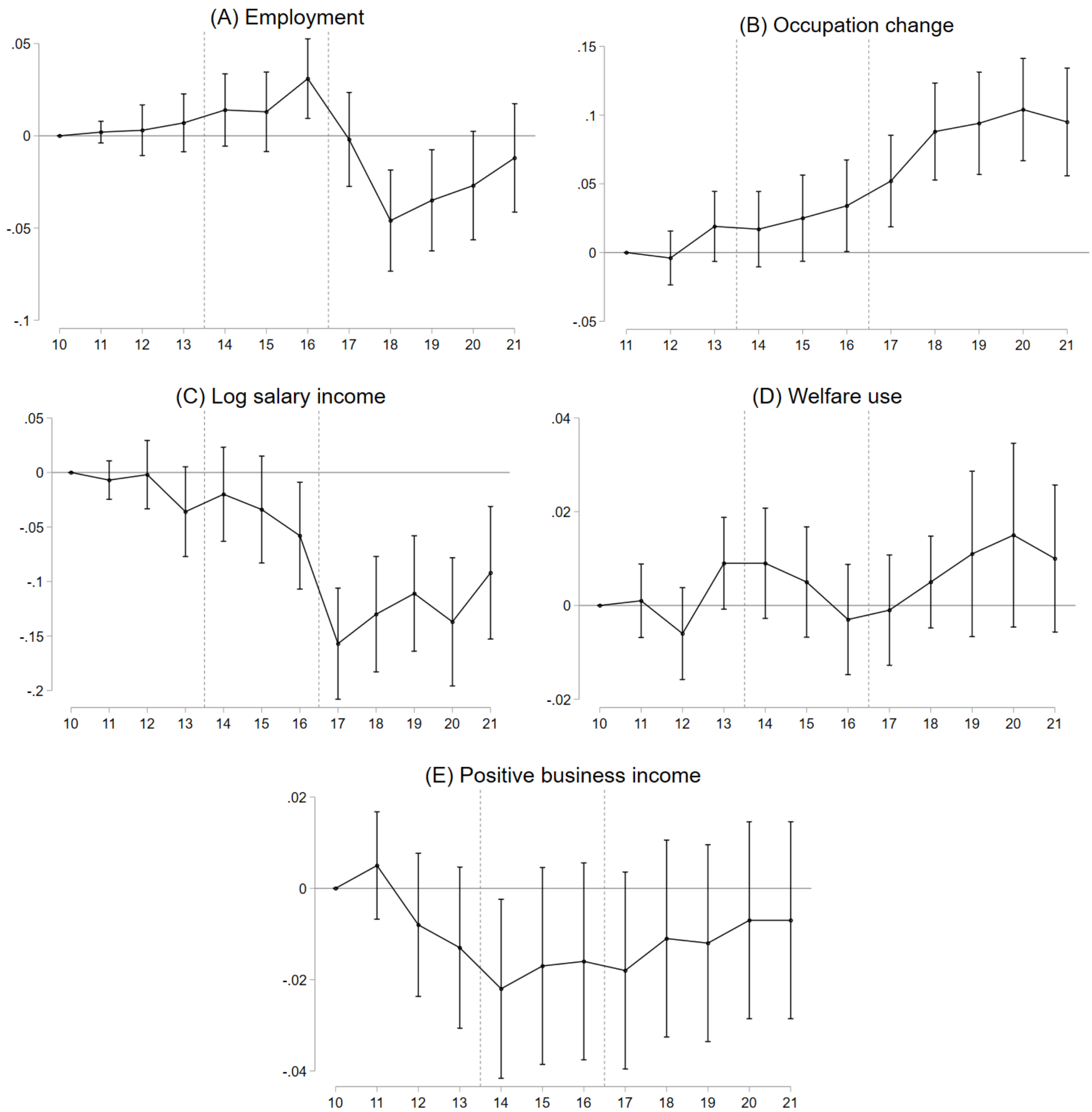


Notes: These graphs are coefficient plots of the DiD event study estimates of the economic outcomes for machinery operators and drivers and labourers. The vertical spikes represent the 95% confidence interval for each coefficient.

The corresponding results for higher skilled workers in Figure 3 point to broadly similar but less pronounced impacts. For example, relatively skilled workers appear to have held on to their jobs to receive maximum redundancy pay – which increased with skill and tenure – in the pre-closure period, and experienced lower joblessness in the post-closure period compared to lower skilled workers (see A). Higher skilled workers also experienced occupation change and reduced earnings, particularly in the post-closure period (see B and C), although at lower levels than their lower skilled counterparts. Earnings in 2017/18, for instance, was around 20% lower than the 2010/11 level, half of the drop experienced by lower skilled workers.

They also did not transition to self-employment unlike lower skilled workers (see E). While we observe higher welfare use among these workers post-closure, the effects are small and statistically insignificant (see D).

Figure 3: Estimated effects on economic outcomes for higher skilled workers



Notes: These graphs are coefficient plots of the DiD event study estimates of the economic outcomes for technicians and trade workers. The vertical spikes represent the 95% confidence interval for each coefficient.

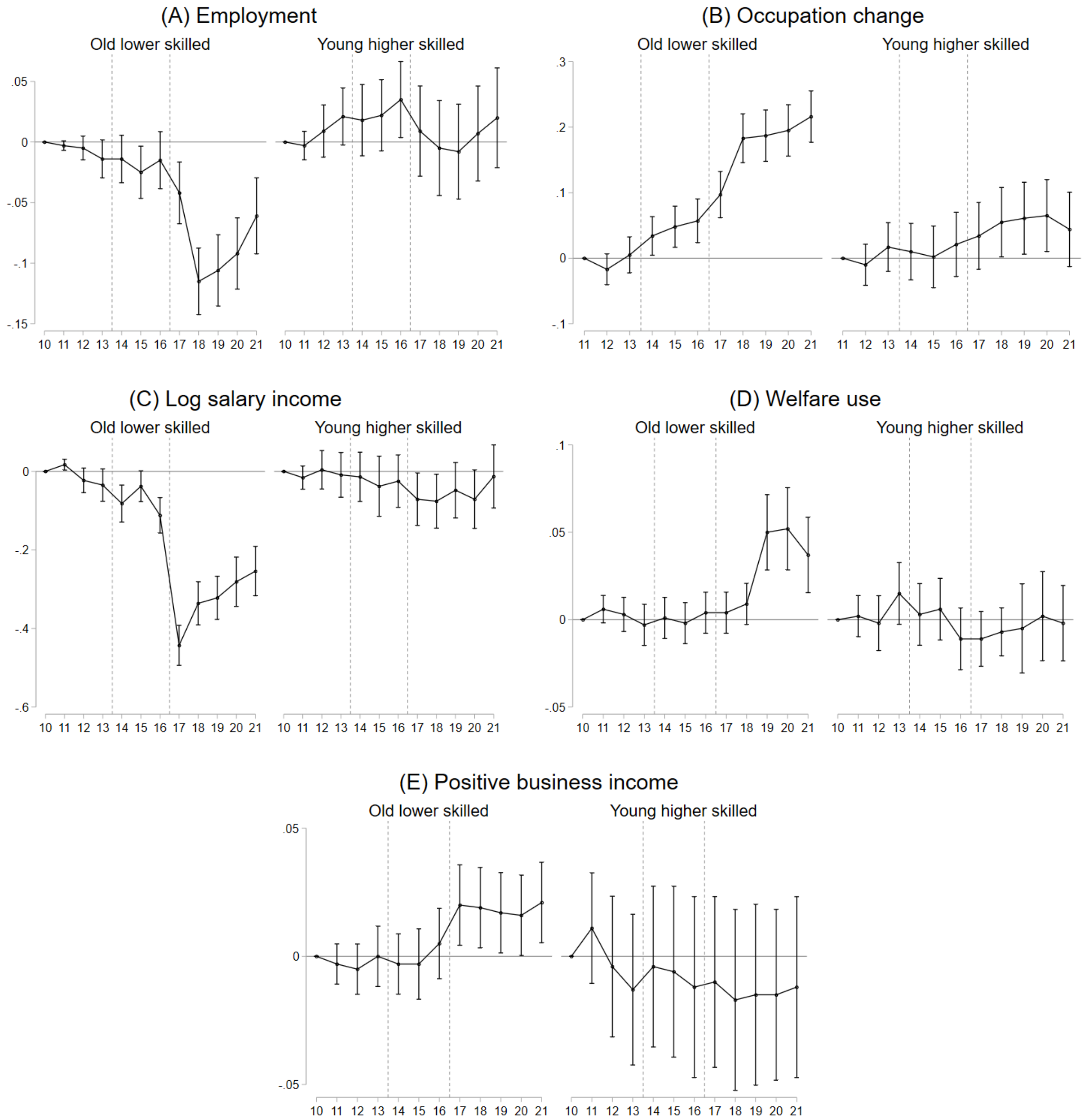
Our findings on employment and earnings effects are broadly comparable to estimates from other studies examining job displacements, defined broadly as the permanent loss of a long-term job due to mass layoffs or establishment closures (Bertheau et al., 2023; Couch and Placzek, 2010; Illing et al., 2024). However, they are much lower than the wage losses of 80-90% documented by Rud et al. (2024) for displaced miners following the UK coal industry closure, who use a similar DiD approach to ours. On job loss, our estimates compare with findings from Europe where the probability of being non-employed five years following job displacement is between 5-20 percentage points larger for displaced workers (Bertheau et al., 2023) and with findings from the US where a 10 percentage point decline in the local manufacturing share reduced local employment rates by 3.7 percentage points for prime-age men (Charles et al., 2019). The negative wage effects are similar to earnings losses of around 30% among displaced workers in Connecticut (Couch and Placzek, 2010), of 25% for workers experiencing job loss in Germany (Illing et al., 2024), and of 40% for laid-off workers in Sweden (Cederlöf, 2024). The wage and occupation instability effects are also consistent with higher occupational switching (to lower-paying occupations) and larger declines in earnings for displaced workers exposed to significant technological change in the US (Braxton and Taska, 2023) and in Spain (Cuccu and Royuela, 2024).

As discussed before, it is likely that older workers were more negatively affected by the industry closure due to factors such as greater difficulty in retraining, less transferability of job-specific skills, and age discrimination in hiring (Batinovic et al., 2023; Carlsson and Eriksson, 2019). Alternatively, we might expect young higher skilled workers to be the least affected, who are likely the easiest to assist in terms of job and career training. To test such dynamics, we further split each skill group sample into those less than and greater than 40 years in 2011, and re-estimate effects. Panels A–E in Figure 4 compare estimates for old lower skilled and young higher skilled workers.[18]

As expected, we observe notably large negative effects for older lower skilled automotive manufacturing workers, while younger higher skilled workers are not strongly affected by the industry shutdown. For instance, this latter group experiences a near-zero effect on employment and a 7% effect on wages in the short-run, compared to a 11 percentage point fall in employment and a 44% reduction in earnings – persisting at a lower level in the longer-run – for older lower skilled workers (see A and C). The increase in the use of unemployment support and the higher likelihood of self-employment in the post-closure period is also limited to lower older skilled workers (see D and E), while the proportion of occupation switchers is over three times larger among this group compared to their younger higher skilled counterparts (see B). Existing studies also document greater reductions in earnings for older compared to younger workers (Athey et al., 2023; Couch and Placzek, 2010; Rud et al., 2024) and for lower compared to higher skilled workers (Braxton and Taska, 2023; Cuccu and Royuela, 2024; Huckfeldt, 2022), following mass layoffs.

[18] Regression estimates for all four groups by skill level and age are reported in Appendix Table .D.2.

Figure 4: Estimated effects on economic outcomes by skill and age



Notes: These graphs are coefficient plots of the DiD event study estimates of the economic outcomes, differentiated by skill level and age. Old lower skilled refers to machinery operators and drivers and labourers aged between 40-55 in 2011. Young higher skilled refers to technicians and trade workers aged between 24-39 in 2011. The vertical spikes represent the 95% confidence interval for each coefficient. The vertical dashed lines indicate when the plant closure announcements were made and when plant operations started ceasing.

5.2 Robustness checks

We test the sensitivity of our results in several ways. First, we test the robustness of our main post-treatment effects to possible violations of parallel trends, following the approach suggested by Rambachan and Roth (2023). Specifically, we construct robust confidence intervals under restrictions on the possible violations of parallel trends, and assess how different the counterfactual trend would have to be relative to the largest pre-treatment violation to invalidate a significant post-treatment effect.

Rambachan and Roth (2023) recommend imposing restrictions and accompanying sensitivity analysis informed by economic and context-specific knowledge. A concern in our setting is that there might be unobserved, industry-specific or macroeconomic shocks that would have affected the car manufacturing industry differently from construction and other manufacturing industries, even in the absence of the car industry closure. For instance, the gradual decline of the automotive manufacturing industry over a long time period and the closure of selected car plants in previous decades might have adversely affected the automotive manufacturing workforce's labour market and health outcomes even if the entire industry had not shutdown. We therefore test possible violations of parallel trends by imposing that industry-specific or macroeconomic shocks affecting car industry workers in the post-treatment period are not too much larger than those in the pre-treatment period. We base our analysis on 'bounds on relative magnitudes' – $\Delta^{RM}(\bar{M})$ – one of the approaches suggested by Rambachan and Roth (2023). This can be formalised by imposing that the post-treatment violation of parallel trends is no more than some constant $\bar{M}$ larger than the maximum violation of parallel trends in the pre-treatment period.[19]

Appendix Figures .C.1 and .C.2 show robust confidence intervals for the treatment effect across the post-treatment period (2014/15–2021/22) for $\Delta^{RM}(\bar{M})$ using different values of $\bar{M}$, for lower skilled and higher skilled workers, respectively. For employment, occupation change, and business income, the "breakdown value" for a null effect is around $\bar{M}$=1.5. This means that our conclusion of a significant effect on these outcomes depends on whether we are willing to restrict that the post-treatment violations of parallel trends can be no larger than 1.5 times the maximal pre-treatment violation of parallel trends. The outcomes of log salary income and welfare use are less robust to these restrictions, where the conclusion of a significant post-treatment effect hinges on the restriction that the post-treatment parallel trends violations can be no larger than the maximal pre-treatment violation ($\bar{M}$=1). Given that the start of treatment in our context did not coincide with any other major economic events that would have differentially affected workers' labour market and mental health outcomes (e.g., a recession), and the relatively large post-treatment effects in comparison to pre-treatment effect magnitudes, we interpret these estimates as fairly robust to possible parallel trend violations (Roth et al., 2023).

We next test the robustness of our main results using different samples. First, we use an alternative control group and a slightly modified treatment group. The control group consists of non-automotive manufacturing and construction industry workers – who work in the same

[19] The other approach, termed 'smoothness restrictions', is to assume that the post-treatment violations of parallel trends cannot deviate too much from a linear extrapolation of the pre-trend. This approach involves imposing restrictions that the slope of the pre-trend can change by no more than M across consecutive periods, if there are concerns about violations of parallel trends that arise due to differences in smoothly evolving secular trends that affect the treated and comparison groups differently (Rambachan and Roth, 2023). This scenario seems less relevant to our context, where imposing that industry-specific shocks follow a smooth trend seems unreasonable.

occupations as those in the automotive manufacturing industry – residing in local labour market regions in the state of New South Wales (NSW). Considering employees from a state different to the car plant states further minimises concerns of possible spillovers from redundant automotive workers into the control industries. We additionally extend our treatment group to include automotive industry workers in areas adjoining the car plant regions, given that control workers are from a different state. These modifications increase our estimation sample from 8,230 to 13,726 individuals, split equally among the treatment and control groups. In the second sample modification, we match treatment and control individuals in our main sample on propensity scores based on occupation and age in 2011, as an alternative to exact matching on occupation.[20] This approach provides us with a (larger) sample of 21,800 individuals, consisting of 5,691 individuals in the treatment group and 16,109 matched controls from other manufacturing and construction industries.

Table 3 reports results of the two robustness specifications for lower skilled workers, and compares them against estimates from the main sample. To aid comparison, we aggregate the yearly effects in terms of post-announcement (2014/15-2015/16) and post-closure (2016/17-2021/22) effects.[21]

The results across the different specifications are largely similar. As with the main sample in column (1), we observe large declines in employment (panel A) and salary income (panel C) among lower skilled automotive industry workers vis-à-vis their control industry counterparts in the post-closure period, across the different samples in columns (2) and (3). We also observe higher occupational switching (panel B), an increased uptake of welfare support (panel D), and higher self-employment (panel E) among this group in the years following the car plant closures. The magnitudes of the effects are comparable across the specifications, indicating an approximate 4 percentage point decline in employment, a 1–2 percentage point increase in occupation change, a 20% decline in earnings in new jobs, a 2–3 percentage point increase in the use of welfare support, and a 1 percentage point increase in positive business income.

[20]We consider matching on all controls with identical propensity scores, as opposed to nearest neighbour matching.

[21]Corresponding estimates for higher skilled workers are reported in Appendix Table .D.3.

Table 3: Estimated effects on economic outcomes of lower skilled workers across different samples

	Main sample	Controls from NSW	Propensity score matching
	(1)	(2)	(3)
A: Employment			
-Post-announcement	-0.016**	-0.010*	-0.007
	(0.007)	(0.006)	(0.007)
-Post-closure	-0.042***	-0.039***	-0.045***
	(0.009)	(0.007)	(0.008)
B: Occupation change			
-Post-announcement	0.051***	0.010	0.027**
	(0.013)	(0.010)	(0.013)
-Post-closure	0.160***	0.130***	0.164***
	(0.014)	(0.011)	(0.014)
C: Log salary income			
-Post-announcement	-0.049***	-0.045***	-0.037**
	(0.015)	(0.011)	(0.015)
-Post-closure	-0.228***	-0.222***	-0.237***
	(0.015)	(0.012)	(0.014)
D: Welfare use			
-Post-announcement	-0.001	0.005	-0.001
	(0.005)	(0.004)	(0.005)
-Post-closure	0.023***	0.031***	0.023***
	(0.005)	(0.004)	(0.005)
E: Positive business income			
-Post-announcement	0.007	-0.001	-0.004
	(0.005)	(0.004)	(0.005)
-Post-closure	0.011*	0.007	0.014**
	(0.006)	(0.004)	(0.006)

Notes: The yearly effects are aggregated into the post-announcement (2014/15-2015/16) and post-closure (2016/17-2021/2022) periods. The main sample in column (1) refers to that used in the main analysis, including treatment workers residing in car plant regions and control workers from the same states in car plant non-adjoining regions, matched based on occupation. The sample in column (2) includes control workers from NSW and treatment workers from car plant and adjoining regions, matched based on occupation. The sample in column (3) is based on the main sample, but the matching of treatment and control workers is done on propensity scores based on occupation and age, as opposed to exact matching on occupation. Workers in all samples are machinery operators and drivers and labourers. Robust standard errors, clustered at the individual level are in parentheses. Controls include individual fixed effects and year fixed effects. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

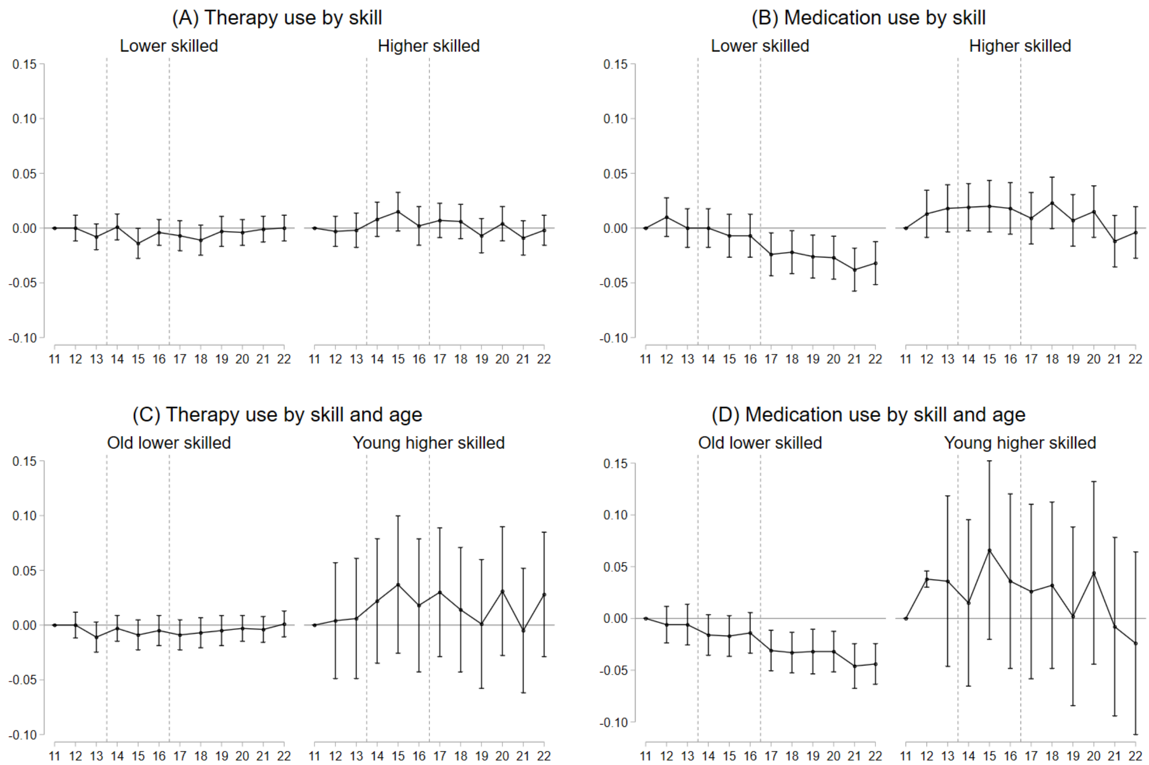
5.3 Health outcomes

To test whether the adverse economic effects experienced by automotive manufacturing workers affected their mental health, panels A and B in Figure 5 present coefficient plots of estimates for psychological therapy service use and mental health medication use, differentiated by skill level.[22] As seen in panel A, there is no extra use of psychological therapy services among treated workers of both skill levels post-treatment, with the estimated effects being small and insignificant. Panel B shows significant *negative* estimated effects for lower skilled workers, indicating *lower* use of antidepressants, anxiolytics, or sedatives among automotive

[22]Regression estimates are reported in Appendix Table .D.4.

industry workers relative to their control industry counterparts in the aftermath of the car industry closure. Panels C and D, which further disaggregate the estimates by age group, show that reduced medication use is concentrated among older lower skilled workers who experienced the adverse economic effects disproportionately. These findings thus suggest that the negative economic impacts experienced by automotive manufacturing industry workers have not translated into poorer mental health outcomes in terms of therapy or drug use. Our health indicators are not fully reflective of actual mental health conditions, and hence our estimates do not necessarily indicate a decline in mental health issues. But they do suggest that the industry closure did not cause an increase in severe mental health problems among affected workers.

Figure 5: Estimated effects on health outcomes by skill level and age



Notes: These graphs are coefficient plots of the DiD event study estimates for the health outcomes, differentiated by skill level (panels A and B) and by skill and age (panels C and D). (Old) lower skilled refers to (40-55-year-old) machinery operators and drivers and labourers (in 2011) and (young) higher skilled refers to (24-39-year-old) technicians and trade workers (in 2011). The vertical spikes represent the 95% confidence interval for each coefficient. The vertical dashed lines indicate when the plant closure announcements were made and when plant operations started ceasing.

This is a surprising result and stands in contrast to the significant negative mental health effects associated with plant closures documented in previous studies (Kuhn et al., 2009; Marcus, 2013; Reichert and Tauchmann, 2017; Schiele and Schmitz, 2016). While most existing studies use self-reported measures of mental health, Kuhn et al. (2009) show evidence of increased drug prescriptions for antidepressants – similar to our measure of medication use

– among men made redundant by plant closures in Austria.

One possible explanation for our findings is the comprehensive employer-provided health and wellbeing support for affected workers, not captured in our data. Regular counselling and therapy sessions offered, for instance, could have lowered the need for similar services provided via the national public system or for mental health-related prescription medications. Such services may have also improved mental health outcomes from what they would have been in the absence of plant closures. Another possibility is that the reduced income of affected workers lowered the use of therapy, given the generally high out-of-pocket costs of psychological services. However, out-of-pocket costs for medications are low and thus negative income effects are unlikely to have had a large effect. We test this mechanism by looking at mental health effects conditional on positive general practitioner (GP) visits. We observe a similar negative effect for lower skilled workers in terms of prescription medication use (see Appendix Figure .D.1), suggesting that the decline in medication use is unlikely to have been driven by financial reasons. Another potential reason for null mental health effects is the relatively low levels of stigma associated with an entire industry closure, as opposed to that associated with specific firm closures. Evidence suggests that the negative wellbeing effect of individual unemployment is less pronounced in areas of high unemployment, given that unemployment might be considered less of a threat to one's identity when others are also unemployed (Green, 2011).[23]

6 Conclusion

In this paper, we explore how the shutdown of Australia's automotive manufacturing industry affected its blue-collar workforce economically and mentally, using administrative data and a DiD event study design. Our main finding is that automotive manufacturing workers either remained unemployed or had to transition to new lower-paying jobs while a small proportion switched to self-employment, compared to similar unaffected workers in the non-automotive manufacturing and construction industries. These effects were disproportionately experienced by lower skilled and older workers who appeared the most vulnerable to the industry closure impacts, while young higher skilled workers were largely unaffected and emerged resilient.

The magnitudes of the effects are comparable to studies examining large-scale job displacement among blue-collar workers, but smaller than earnings losses documented for workers made redundant by a similar whole-of-industry closure in the UK. The lower wage losses documented in our setting might be partly explained by the substantial three-year advance

[23]Our findings on health impacts are similar to those from a survey conducted by Wallis & ACIL Allen (2020) that followed a sample of retrenched workers from Ford and Toyota for the first 12 months following car company closures. Most of the surveyed Ford ex-employees reported low stress levels which were generally at or below the national average, and over 70% of Toyota ex-employees reported to be of good emotional health. Wallis & ACIL Allen (2020) attribute these positive findings to the significant investments made in mental health and wellbeing services of workers and the long transition period provided.

notice of car plant closures provided to workers, compared to the rapid dissolution of UK's coal industry. Using Swedish administrative data on layoff notifications, Cederlöf et al. (2024) show that workers eligible for extended mandatory notice policies are less exposed to non-employment spells and subsequently obtain well-paying jobs. This study also shows that employment search following advance notice allows workers to target high-quality jobs, avoiding significant job losses. The sizable job losses documented in our setting despite advance notice can be attributed to our focus on an entire industry closure and its effects on blue-collar workers, in comparison to Cederlöf et al. (2024)'s sample of retrenched white-collar workers in private sector firms, for whom finding better alternative jobs might typically be easier.

In contrast to economic effects, we do not find evidence of increased mental healthcare use among affected workers relative to control industry workers, unlike significant negative health effects observed in prior studies. One potential explanation for this surprising result is that a combination of best practice examples – including the early notification of plant closures with extensive lead time, generous redundancy payments, and comprehensive support systems involving health and wellbeing care, resilience training, and sustained post-closure services – helped minimise negative impacts on mental health caused by the adverse economic consequences of the layoffs. The counselling, health, and wellbeing services provided both before and after plant closures appear unique to our setting and were largely absent in the US context. For instance, there is some evidence to suggest that undervaluing its workers was one factor characterising GM's long descent in the US (Guilford, 2018), while unexpected job loss following plant closures is cited as one probable explanation for opioid overdoses among workers in affected manufacturing counties (Glatter, 2019). Our findings could also reflect the unique context in Australia where the entire industry closed down, triggering less of a scarring effect associated with job loss as opposed to selected car plant closures in other settings.

The results of this study hold several important policy implications, especially in the wake of future major industrial changes such as the closure of coal and gas power plants and associated mining industries. Approximately one-third of coal-fired power stations closed in Australia in the past decade, for instance, with more closures expected to occur in the future (Andrews et al., 2023; Burke et al., 2019). On the one hand, the higher unemployment levels and earnings losses experienced by redundant workers despite the extensive lead time and wide-ranging support provided, is suggestive of the challenges in reskilling and transferring skills sets. Our results show that it is particularly vital to assist older lower skilled workers who experience these negative effects disproportionately and are the least likely to be able to transition to a new career. On the other hand, the substantially smaller earnings losses compared to the UK coal industry closure, and null mental health effects, underscore the importance of holistic, well-targeted, and implemented support systems – extending beyond career and job support to health and wellbeing support – in containing adverse impacts associated with mass layoffs.

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.A Appendix A: Car plant closures and support services offered

Table .A.1: Car plant closure announcement and closure dates

Company	Automotive facility	Closure announcement	Closure date
Ford	Production plant, Broadmeadows	23 May 2013	7 October 2016
	Broadmeadows and Geelong plants	May 2013	July 2017
GM Holden	Cruze Production, Elizabeth	December 2013	7 October 2016
	Engine Plant, Port Melbourne		29 November 2016
	Production Plant, Elizabeth		20 October 2017
Toyota	Production Plant, Altona	February 2014	3 October 2017

Source: Information provided by Ford Australia, GM Holden, and Toyota Motor Corporation Australia, as cited in Wallis & ACIL Allen (2020).

Table .A.2: Summary of support services provided for car industry workers

Jurisdiction	Program partners	Program/initiative	Services offered
Australian Government Ford Transition Program	Department of Education and Training Delivered by Auto Skills Australia for Ford	Ford Transition Program $5.25 million to support the transition of Ford workers from their current jobs into other meaningful employment	Support, counselling and information referrals, careers and training advice, skills recognition and training, job search assistance
Australian Government $155 mn Growth fund	Department of Education and Training Delivered by Holden and Toyota	Skills and Training Initiative $30 million to assist Holden, Toyota and Tier 1 supply chain workers	Skills recognition and training while still employed
		Toyota DRIVE Program $15 million to establish Growth Fund and dedicated transition centres in Victoria and Sydney for Toyota workers and Tier 1 suppliers	Information sessions and workshops, career and training advice, skilling and training, including full funding for further education and training, and job support
		Holden Skills and Training Initiative $15 million to establish Holden Transition Centres for Holden workers in South Australia and Victoria	Counselling and information, careers and training advice, labour market information and job search assistance
	Department of Employment	Automotive Industry Structural Adjustment Program (AISAP) $15 million funding through the jobactive employment services network, targetting all retrenched workers	Résumé preparation, job applications, interview skills, training to obtain tickets or licenses, work experience, information on suitable jobs and referral to vacancies, other assistance with job search
	Department of Industry, Innovation and Science	Automotive Diversification Program $20 million to assist automotive supply chain firms capable of diversifying to enter new markets	Assistance to diversify, develop new products and processes, and expand into new markets
	Department of Industry, Innovation and Science	Next Generation Manufacturing Investment Programme $90 million to accelerate private sector investment in high value non-automotive manufacturing industries	Defense and aerospace, pharmaceuticals, medical devices, precision engineering and engineered timber building products
Victorian Government	Victorian Department of Education	Victorian Department of Education Automotive Supply Chain Training Initiative $30 million for skills and career development of automotive supply chain workers	Up-skill and re-skill workers, support businesses to restructure into new opportunities, establish two new Skills and Jobs Centres for workers, job seekers and businesses to access a range of Government support, career advice, referrals to other job services, skills assessments and training plans, and 5 specialist automotive Skills and Jobs Centres (SJCs)
	Victorian Department of Economic Development, Jobs, Transport and Resources	Automotive Supply Chain Transition Program $5 million for automotive supply chain firms	Assistance to transition to new sectors by developing new products or finding new markets through new partnering or acquisitions opportunities
		Local Industry Fund for Transition (LIFT) program $33 million for affected communities	Assist businesses in the supply chain to retain/expand their workforce, encourage investment to help create new sustainable jobs and economic activity.

Continued on next page

Table 2.A.2 continued from previous page

Jurisdiction	Program partners	Program/initiative	Services offered
South Australian Government	SA Department of State Development	Automotive Workers in Transition Program $7.8 million for automotive supply chain workers (and spouses/partners)	Career counselling, recognition of prior learning, vocational training and skills development, job preparation advice including digital literacy and workshops, support and advice for retirement and financial planning, resilience training through the South Australian Health and Medical Research Institute and the Port Adelaide Football Club Resilience Program, access to subsidised training in priority areas, Beyond Auto confidential service focusing on wellbeing of workers and their families, connecting workers with personal, financial, and employment services, Drive Your Future Job Connect - a free service connecting former automotive supply chain workers with job opportunities, intensive case management for families in crisis, a new Disability Employment Hub to train former automotive workers.
Commonwealth Government Innovation and Investment Funds	Australian Government Department of Industry, Innovation and Science with Victorian Government and Ford contributions	Melbourne's North Innovation and Investment Fund $24.5 million to support new jobs and investment by local businesses	Support for innovative job creation projects that strengthen and diversify their respective regional economies and employment bases.
	Australian Government Department of Industry, Innovation and Science with Victorian Government, Ford and Alcoa contributions	Geelong Region Innovation and Investment Fund $29.5 million to support new jobs and investment by local businesses	
	Advanced Manufacturing Fund	$100 million to help companies in Victoria and South Australia transition to advanced manufacturing through capital investments to improve efficiencies and competitiveness of firms.	Support for small-scale research projects, Cooperative Research Centre for large-scale advanced manufacturing research projects, Innovation Labs to maintain automotive design and engineering excellence at universities, technology institutions and in industry, removing tariffs on imported vehicle prototypes and components.

Source: Wallis & ACIL Allen (2020).

.B Appendix B: Industries and occupations in the treatment and control groups

Table .B.1: Industry codes and descriptions

Industry code	Description
A: Automotive manufacturing	
23	Motor Vehicle and Motor Vehicle Part Manufacturing
2311	Motor Vehicle Manufacturing
2312	Motor Vehicle Body and Trailer Manufacturing
2313	Automotive Electrical Component Manufacturing
2319	Other Motor Vehicle Parts Manufacturing
B: Other manufacturing and construction	
B1: Other manufacturing	
11	Food Products Manufacturing
12	Beverage and Tobacco Products Manufacturing
13	Textile, Leather, Clothing and Footwear Manufacturing
14	Wood Products Manufacturing
15	Pulp, Paper and Converted Paper Products Manufacturing
16	Printing (including the Reproduction of Recorded Media)
17	Petroleum and Coal Products Manufacturing
18	Basic Chemical and Chemical Products Manufacturing
24	Machinery and Equipment Manufacturing
25	Furniture and Other Manufacturing
B2: Construction	
30	Building Construction
31	Heavy and Civil Engineering Construction
32	Construction Services
C: Auto supply chain subindustries excluded	
19	Polymer Product and Rubber Product Manufacturing
20	Non-Metallic Mineral Product Manufacturing
21	Primary Metal and Metal Product Manufacturing
22	Fabricated Metal Product Manufacturing

Notes: Industry groups are based on information provided in the 2011 Census. Panel A (B) lists the industry groups of workers in the treatment (control) group. Other manufacturing refers to all manufacturing sectors except automotive manufacturing and auto supply chain subindustries. Workers in industry groups in panel C are not included in the sample.

Table .B.2: Frequent four-digit occupations among the treatment sample and corresponding number of controls

Occupation code	Description	Unmatched sample		Matched sample
		Treatment	Control	
(1)	(2)	(3)	(4)	(5)
8322	Product assemblers	2118	810	810
7411	Storepersons	366	1147	366
3232	Metal Fitters and Machinists	334	1443	334
8393	Product Quality Controllers	316	316	316
7213	Forklift Drivers	284	1069	284
3223	Structural Steel and Welding Trades Workers	263	939	263
3212	Motor Mechanics	234	157	157
3411	Electricians	188	2798	188
3242	Vehicle Body Builders and Trimmers	158	31	31
7123	Engineering Production Workers	155	378	155
3234	Toolmakers and Engineering Patternmakers	135	195	135
8391	Metal Engineering Process Workers	110	111	110
7100	Machine and Stationary Plant Operators	93	350	93
7116	Sewing Machinists	78	302	78
8300	Factory Process Workers	74	437	74
7110	Clay, Concrete, Glass and Stone Processing Machine Operators	64	508	64
7112	Industrial Spraypainters	56	115	56
3243	Vehicle Painters	53	30	30
3941	Cabinetmakers	37	874	37
3125	Mechanical Engineering Draftspersons and Technicians	35	80	35

Notes: Occupation codes are those reported in the 2010/11 financial year. Treatment and control workers in the unmatched sample [columns (3) and (4)] refer to those in the original sample before matching on occupation. The matched sample in column (5) refers to the number of workers each in each group used in the analysis. This sample is derived by matching treatment and control observations with the same 4-digit occupation code, which produces a matching result that has the same number of treated and control in each matched occupation group, by randomly dropping observations.

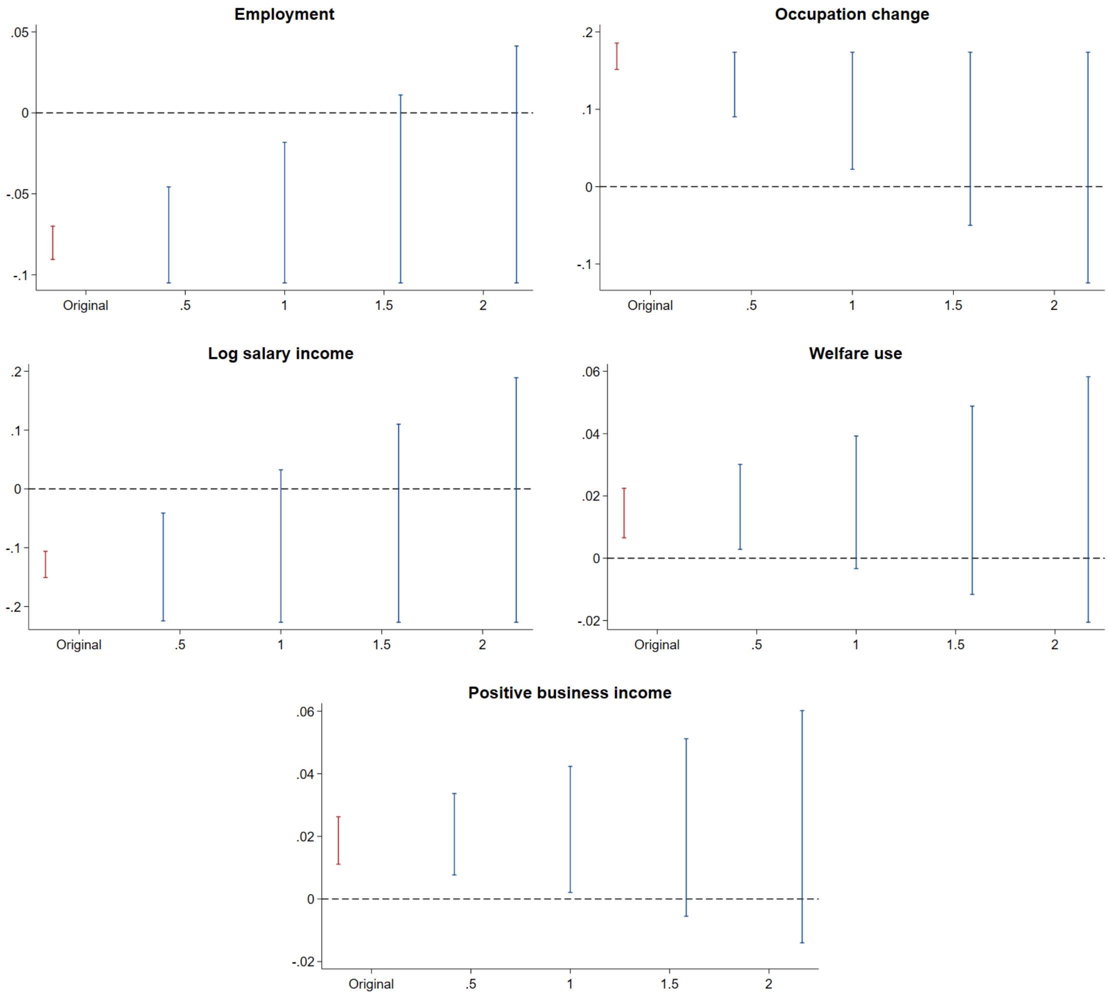
.C Appendix C: Testing parallel trends assumptions

Table .C.1: F-tests of joint significance of pre-trend coefficients

	Lower skilled	Higher skilled
A: Economic outcomes		
Employment	F(3,5367)=0.97 Prob>F=0.4055	F(3,2861)=0.30 Prob>F=0.8258
Occupation change	F(2,5090)=1.72 Prob>F=0.1787	F(2,2724)=2.83 Prob>F=0.0592
Salary income	F(3,5367)=7.72 Prob>F=0.0000	F(3,2861)=1.33 Prob>F=0.2621
Welfare use	F(3,5367)=0.78 Prob>F=0.5026	F(3,2861)=4.02 Prob>F =0.0073
Business income	F(3,5367)=1.09 Prob>F=0.3521	F(3,2861)=1.62 Prob>F=0.1816
B: Health outcomes		
Psychological therapy use	F(2,13296)=2.16 Prob>F=0.1152	F(2,10498)=0.30 Prob>F=0.7408
Mental health medication use	F(2,15124)=0.78 Prob>F=0.4578	F(2,12716)=1.44 Prob>F=0.2367

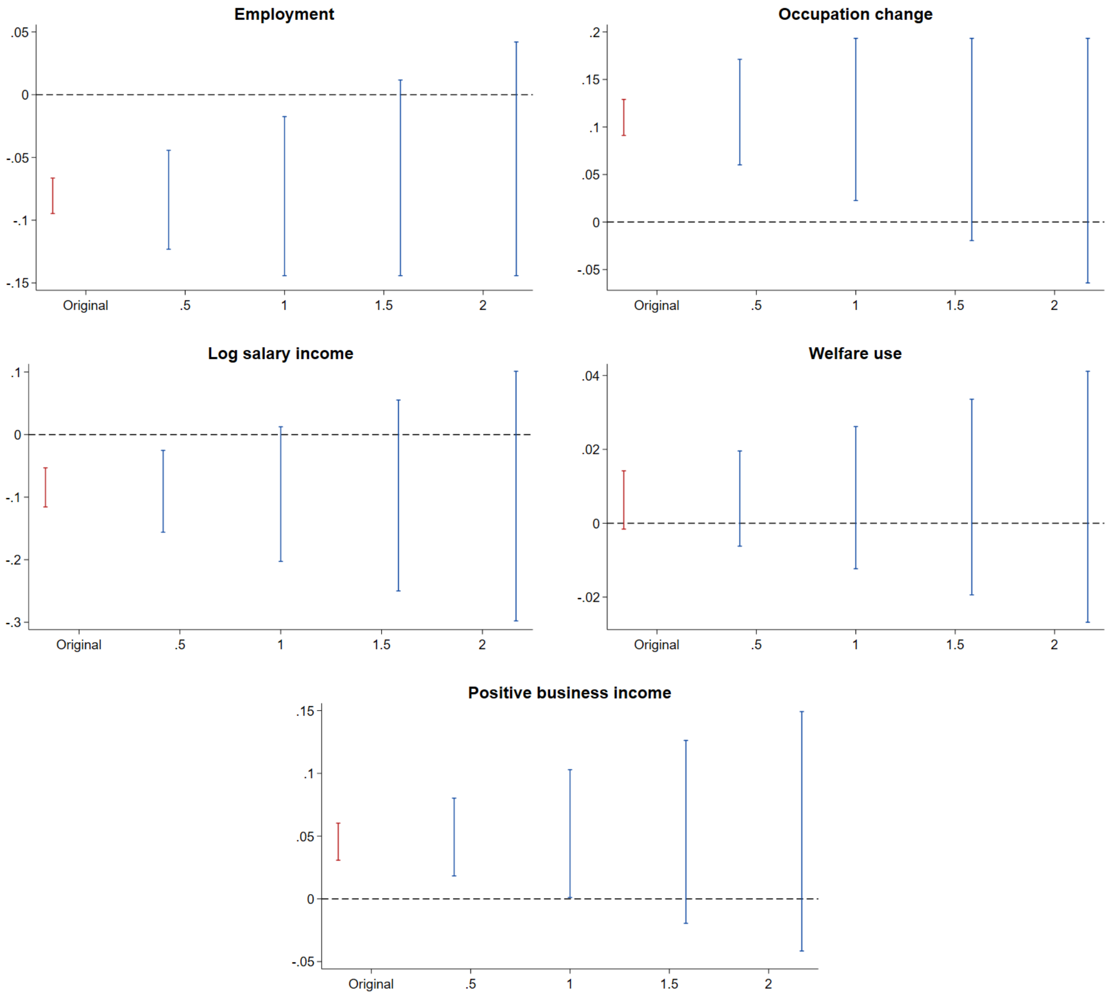
Notes: This table shows F-statistics and corresponding p-values for F-tests of joint significance of pre-trend coefficients, across the 2011/12-2013/14 period, for the economic and health outcomes. Lower skilled refers to machinery operators and drivers and labourers and higher skilled refers to technicians and trade workers. For most outcomes there is no significant pre-trend at the 1% level of significance, where the null hypothesis of a zero effect cannot be rejected. The exceptions are salary income for the lower skilled and welfare use for the higher skilled.

Figure .C.1: Robust confidence intervals for post-treatment economic effects of lower skilled workers



Notes: These figures show 95% robust confidence intervals for the treatment effect for machinery operators and drivers and labourers across the post-treatment period (2014/15-2021/2022) for $\Delta^{RM}(\bar{M})$ using different values of $\bar{M}$. The first figure on employment implies that if we impose $\bar{M}$=1, meaning that we restrict the post-treatment violations of parallel trends to be equal to the maximal pretreatment violation of parallel trends, then we obtain a robust confidence interval of [-0.105, -0.018] for the causal effect on the probability of being employed in the post-treatment period. Looking further to the right, we see that the "breakdown value" for a null effect is around $\bar{M}$=1.5. Thus, our conclusion of a significant effect on employment depends on whether we are willing to restrict that the post-treatment violation of parallel trends can be no more than 1.5 times the maximal pre-treatment violation. The same conclusion applies to occupation change and positive business income. For welfare use and log salary income, the "breakdown value" of a null effect is around $\bar{M}$=1, meaning that a significant post-treatment effect depends on whether we are willing to restrict that the post-treatment violations of parallel trends can be no larger than the maximal pre-treatment violation.

Figure .C.2: Robust confidence intervals for post-treatment economic effects of higher skilled workers



Notes: These figures show 95% robust confidence intervals for the treatment effect for technicians and trade workers across the post-treatment period (2014/15-2021/2022) for $\Delta^{RM}(\bar{M})$ using different values of $\bar{M}$. The first figure on employment implies that if we impose $\bar{M}$=1, meaning that we restrict the post-treatment violations of parallel trends to be equal to the maximal pretreatment violation of parallel trends, then we obtain a robust confidence interval of [-0.144, -0.017] for the causal effect on the probability of being employed in the post-treatment period. Looking further to the right, we see that the "breakdown value" for a null effect is around $\bar{M}$=1.5. Thus, our conclusion of a significant effect on employment depends on whether we are willing to restrict that the post-treatment violation of parallel trends can be no more than 1.5 times the maximal pre-treatment violation. The same conclusion applies to occupation change and positive business income. For log salary income (welfare use), the "breakdown value" of a null effect is around $\bar{M}$=1 ($\bar{M}$=0.5), meaning that a significant post-treatment effect depends on whether we are willing to restrict that the post-treatment violations of parallel trends can be no larger than (is half the value of) the maximal pre-treatment violation.

.D Appendix D: Estimated effects on economic and health outcomes

Table .D.1: Estimated effects on economic outcomes

	Full sample	Higher skilled	Lower skilled
A: Employment			
2011/12	0.002	0.002	0.001
	(0.002)	(0.003)	(0.002)
2012/13	0.002	0.003	0.002
	(0.004)	(0.007)	(0.005)
2013/14	-0.003	0.007	-0.007
	(0.005)	(0.008)	(0.006)
2014/15	-0.003	0.014	-0.013
	(0.006)	(0.010)	(0.008)
2015/16	-0.008	0.013	-0.020**
	(0.007)	(0.011)	(0.008)
2016/17	0.006	0.031***	-0.008
	(0.007)	(0.011)	(0.009)
2017/18	-0.015*	-0.002	-0.022**
	(0.008)	(0.013)	(0.010)
2018/19	-0.064***	-0.046***	-0.074***
	(0.009)	(0.014)	(0.011)
2019/20	-0.058***	-0.035**	-0.070***
	(0.009)	(0.014)	(0.011)
2020/21	-0.045***	-0.027*	-0.054***
	(0.009)	(0.015)	(0.011)
2021/22	-0.021**	-0.012	-0.026**
	(0.009)	(0.015)	(0.012)
Observations	98,124	34,125	63,999
B: Occupation change			
2012/13	-0.011	-0.004	-0.014
	(0.007)	(0.010)	(0.010)
2013/14	0.006	0.019	-0.002
	(0.009)	(0.013)	(0.012)
2014/15	0.024**	0.017	0.027**
	(0.010)	(0.014)	(0.013)
2015/16	0.039***	0.025	0.047***
	(0.010)	(0.016)	(0.013)
2016/17	0.048***	0.034**	0.056***
	(0.011)	(0.017)	(0.014)
2017/18	0.082***	0.052***	0.099***
	(0.011)	(0.017)	(0.015)
2018/19	0.140***	0.088***	0.169***
	(0.012)	(0.018)	(0.015)
2019/20	0.144***	0.094***	0.172***
	(0.012)	(0.019)	(0.016)
2020/21	0.152***	0.104***	0.180***
	(0.012)	(0.019)	(0.016)
2021/22	0.158***	0.095***	0.193***
	(0.013)	(0.020)	(0.016)
Observations	74,477	26,279	48,198
C: Salary income			
2011/12	0.015***	-0.007	0.026***
	(0.005)	(0.009)	(0.007)
2012/13	-0.006	-0.002	-0.009
	(0.010)	(0.016)	(0.013)
2013/14	-0.027**	-0.036*	-0.023
	(0.013)	(0.021)	(0.016)
2014/15	-0.047***	-0.048**	-0.050***
	(0.015)	(0.023)	(0.017)
2015/16	-0.066***	-0.062**	-0.069***
	(0.016)	(0.025)	(0.018)
2016/17	-0.091***	-0.075***	-0.100***
	(0.017)	(0.027)	(0.021)

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Table .D.1 continued from previous page

	Full sample	Higher skilled	Lower skilled
2017/18	-0.216***	-0.130***	-0.264***
	(0.016)	(0.027)	(0.020)
2019/20	-0.208***	-0.111***	-0.261***
	(0.017)	(0.027)	(0.021)
2020/21	-0.187***	-0.137***	-0.216***
	(0.018)	(0.030)	(0.023)
2021/22	-0.160***	-0.092***	-0.197***
	(0.018)	(0.031)	(0.023)
Observations	87,041	30,546	56,495
D: Welfare use			
2011/12	0.003	0.001	0.004
	(0.003)	(0.004)	(0.004)
2012/13	0.000	-0.006	0.004
	(0.003)	(0.005)	(0.004)
2013/14	0.003	0.009*	-0.001
	(0.004)	(0.005)	(0.005)
2014/15	0.003	0.009	0.001
	(0.004)	(0.006)	(0.005)
2015/16	0.001	0.005	-0.002
	(0.004)	(0.006)	(0.005)
2016/17	0.003	-0.003	0.007
	(0.004)	(0.006)	(0.005)
2017/18	0.004	-0.001	0.007
	(0.004)	(0.006)	(0.005)
2018/19	0.008**	0.005	0.010*
	(0.004)	(0.005)	(0.005)
2019/20	0.035***	0.011	0.047***
	(0.007)	(0.009)	(0.009)
2020/21	0.032***	0.015	0.042***
	(0.007)	(0.010)	(0.009)
2021/22	0.021***	0.01	0.026***
	(0.006)	(0.008)	(0.008)
Observations	98,124	34,125	63,999
E: Positive business income			
2011/12	0.000	0.005	-0.003
	(0.003)	(0.006)	(0.004)
2012/13	-0.008*	-0.008	-0.008*
	(0.004)	(0.008)	(0.005)
2013/14	-0.007	-0.013	-0.004
	(0.004)	(0.009)	(0.005)
2014/15	-0.013***	-0.022**	-0.009*
	(0.005)	(0.010)	(0.005)
2015/16	-0.009*	-0.017*	-0.005
	(0.005)	(0.011)	(0.006)
2016/17	-0.006	-0.016	-0.001
	(0.006)	(0.011)	(0.006)
2017/18	0.005	-0.018	0.017***
	(0.006)	(0.011)	(0.007)
2018/19	0.005	-0.011	0.014**
	(0.006)	(0.011)	(0.007)
2019/20	0.003	-0.012	0.011
	(0.006)	(0.011)	(0.007)
2020/21	0.004	-0.007	0.011
	(0.006)	(0.011)	(0.007)
2021/22	0.006	-0.007	0.013*
	(0.006)	(0.011)	(0.007)
Observations	98,124	34,125	63,999

Notes: The coefficients (time dummies interacted with treatment status) are compared to 2010/11, the base year, for automotive vis-à-vis construction and non-automotive manufacturing industry workers. Higher skilled refers to technicians and trade workers and lower skilled refers to machinery operators and drivers and labourers. Robust standard errors, clustered at the individual level are in parentheses. Controls include individual fixed effects and year fixed effects. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table .D.2: Estimated effects on economic outcomes by skill and age

	Higher skilled		Lower skilled	
	24-39 years	40-55 years	24-39 years	40-55 years
A: Employment				
2011/12	-0.003	0.006	0.010**	-0.003
	(0.006)	(0.004)	(0.005)	(0.002)
2012/13	0.009	-0.002	0.014	-0.005
	(0.011)	(0.009)	(0.010)	(0.005)
2013/14	0.021*	-0.008	0.004	-0.014*
	(0.012)	(0.011)	(0.011)	(0.008)
2014/15	0.018	0.008	-0.01	-0.014
	(0.015)	(0.013)	(0.013)	(0.010)
2015/16	0.022	0.004	-0.011	-0.025**
	(0.015)	(0.015)	(0.014)	(0.011)
2016/17	0.035**	0.027*	0.003	-0.015
	(0.016)	(0.016)	(0.014)	(0.012)
2017/18	0.009	-0.01	0.007	-0.042***
	(0.019)	(0.019)	(0.015)	(0.013)
2018/19	-0.005	-0.080***	-0.013	-0.115***
	(0.020)	(0.020)	(0.016)	(0.014)
2019/20	-0.008	-0.054**	-0.02	-0.106***
	(0.020)	(0.021)	(0.016)	(0.015)
2020/21	0.007	-0.051**	-0.002	-0.092***
	(0.020)	(0.021)	(0.016)	(0.015)
2021/22	0.02	-0.034	0.02	-0.061***
	(0.021)	(0.023)	(0.016)	(0.016)
Observations	16,520	17,605	24,660	39,339
B: Occupation change				
2012/13	-0.01	0.004	-0.012	-0.017
	(0.016)	(0.013)	(0.018)	(0.012)
2013/14	0.017	0.023	-0.017	0.005
	(0.019)	(0.017)	(0.021)	(0.014)
2014/15	0.010	0.027	0.012	0.034**
	(0.022)	(0.019)	(0.022)	(0.015)
2015/16	0.002	0.049**	0.039*	0.048***
	(0.024)	(0.021)	(0.023)	(0.016)
2016/17	0.021	0.051**	0.047*	0.057***
	(0.025)	(0.022)	(0.024)	(0.017)
2017/18	0.034	0.073***	0.092***	0.097***
	(0.026)	(0.023)	(0.025)	(0.018)
2018/19	0.055**	0.122***	0.139***	0.183***
	(0.027)	(0.024)	(0.025)	(0.019)
2019/20	0.061**	0.128***	0.142***	0.187***
	(0.028)	(0.026)	(0.026)	(0.020)
2020/21	0.065**	0.145***	0.150***	0.195***
	(0.028)	(0.026)	(0.026)	(0.020)
2021/22	0.044	0.149***	0.154***	0.216***
	(0.029)	(0.027)	(0.026)	(0.020)
Observations	12,652	13,627	18,916	29,282
C: Salary income				
2011/12	-0.016	0.005	0.041***	0.017**
	(0.015)	(0.010)	(0.013)	(0.007)
2012/13	0.004	-0.001	0.014	-0.023
	(0.025)	(0.019)	(0.023)	(0.016)
2013/14	-0.009	-0.049	-0.006	-0.035*
	(0.029)	(0.030)	(0.026)	(0.021)
2014/15	-0.014	-0.015	-0.033	-0.082***
	(0.032)	(0.029)	(0.028)	(0.024)
2015/16	-0.038	-0.021	-0.04	-0.038*
	(0.039)	(0.031)	(0.027)	(0.020)
2016/17	-0.025	-0.068*	-0.053*	-0.112***
	(0.034)	(0.036)	(0.028)	(0.023)
2017/18	-0.071**	-0.209***	-0.247***	-0.443***
	(0.034)	(0.038)	(0.033)	(0.026)
2018/19	-0.076**	-0.157***	-0.180***	-0.336***
	(0.035)	(0.041)	(0.029)	(0.028)
2019/20	-0.048	-0.147***	-0.193***	-0.322***

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Table .D.2 continued from previous page

	Higher skilled		Lower skilled	
	24-39 years	40-55 years	24-39 years	40-55 years
	(0.036)	(0.039)	(0.033)	(0.028)
2020/21	-0.071*	-0.171***	-0.151***	-0.281***
	(0.038)	(0.044)	(0.034)	(0.032)
2021/22	-0.013	-0.138***	-0.145***	-0.254***
	(0.041)	(0.045)	(0.032)	(0.032)
Observations	14,899	15,647	22,176	34,319
D: Welfare use				
2011/12	0.002	0.000	0.001	0.006
	(0.006)	(0.005)	(0.007)	(0.004)
2012/13	-0.002	-0.009	0.004	0.003
	(0.008)	(0.007)	(0.008)	(0.005)
2013/14	0.015	0.006	0.002	-0.003
	(0.009)	(0.006)	(0.009)	(0.006)
2014/15	0.003	0.014*	-0.001	0.001
	(0.009)	(0.008)	(0.009)	(0.006)
2015/16	0.006	0.004	-0.001	-0.002
	(0.009)	(0.009)	(0.009)	(0.006)
2016/17	-0.011	0.004	0.011	0.004
	(0.009)	(0.008)	(0.009)	(0.006)
2017/18	-0.011	0.008	0.013	0.004
	(0.008)	(0.008)	(0.008)	(0.006)
2018/19	-0.007	0.016**	0.012	0.009
	(0.007)	(0.007)	(0.008)	(0.006)
2019/20	-0.005	0.025**	0.043***	0.050***
	(0.013)	(0.013)	(0.014)	(0.011)
2020/21	0.002	0.023*	0.028*	0.052***
	(0.013)	(0.014)	(0.015)	(0.012)
2021/22	-0.002	0.019	0.012	0.037***
	(0.011)	(0.012)	(0.012)	(0.011)
Observations	16520	17605	24660	39339
E: Positive business income				
2011/12	0.011	-0.001	-0.002	-0.003
	(0.011)	(0.007)	(0.007)	(0.004)
2012/13	-0.004	-0.009	-0.013	-0.005
	(0.014)	(0.009)	(0.008)	(0.005)
2013/14	-0.013	-0.009	-0.012	0.000
	(0.015)	(0.010)	(0.009)	(0.006)
2014/15	-0.004	-0.034***	-0.019*	-0.003
	(0.016)	(0.012)	(0.010)	(0.006)
2015/16	-0.006	-0.024*	-0.01	-0.003
	(0.017)	(0.013)	(0.011)	(0.007)
2016/17	-0.012	-0.016	-0.011	0.005
	(0.018)	(0.014)	(0.012)	(0.007)
2017/18	-0.010	-0.023*	0.012	0.020**
	(0.017)	(0.014)	(0.012)	(0.008)
2018/19	-0.017	-0.002	0.004	0.019**
	(0.018)	(0.014)	(0.012)	(0.008)
2019/20	-0.015	-0.004	-0.001	0.017**
	(0.018)	(0.013)	(0.012)	(0.008)
2020/21	-0.015	0.004	0.001	0.016*
	(0.017)	(0.013)	(0.012)	(0.008)
2021/22	-0.012	0.002	-0.003	0.021***
	(0.018)	(0.013)	(0.012)	(0.008)
Observations	16,520	17,605	24,660	39,339

Notes: The coefficients (time dummies interacted with treatment status) are compared to 2010/11, the base year, for automotive vis-à-vis construction and non-automotive manufacturing industry workers. Higher skilled refers to technicians and trade workers and lower skilled refers to machinery operators and drivers and labourers. Ages refer to those in 2011. Robust standard errors, clustered at the individual level are in parentheses. Controls include individual fixed effects and year fixed effects. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table .D.3: Estimated effects on economic outcomes of higher skilled workers across different samples

	Main sample	Controls from NSW	Propensity score matching
	(1)	(2)	(3)
A: Employment			
-Post-announcement	0.014	0.011	0.008
	(0.009)	(0.007)	(0.010)
-Post-closure	-0.015	-0.003	-0.011
	(0.011)	(0.009)	(0.012)
B: Occupation change			
-Post-announcement	0.029*	0.017	0.043***
	(0.016)	(0.012)	(0.016)
-Post-closure	0.086***	0.042***	0.098***
	(0.017)	(0.014)	(0.017)
C: Log salary income			
-Post-announcement	-0.027	0.008	-0.025
	(0.020)	(0.016)	(0.020)
-Post-closure	-0.113***	-0.071***	-0.092***
	(0.021)	(0.016)	(0.024)
D: Welfare use			
-Post-announcement	0.007	-0.002	0.002
	(0.005)	(0.004)	(0.007)
-Post-closure	0.006	0.004	0.005
	(0.005)	(0.004)	(0.007)
E: Positive business income			
-Post-announcement	-0.020**	-0.011	-0.010
	(0.010)	(0.007)	(0.009)
-Post-closure	-0.012	-0.002	0.001
	(0.009)	(0.007)	(0.010)

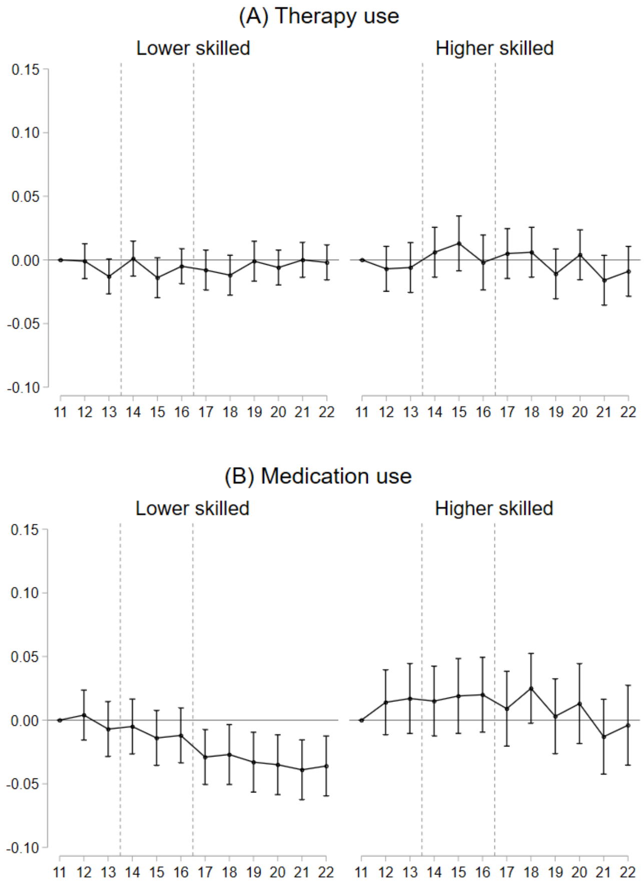
Notes: The yearly effects are aggregated into the post-announcement (2014/15-2015/16) and post-closure (2016/17-2021/2022) periods. The main sample in column (1) refers to that used in the main analysis, including treatment workers residing in car plant regions and control workers from the same states in car plant non-adjoining regions, matched based on occupation. The sample in column (2) includes control workers from NSW and treatment workers from car plant and adjoining regions, matched based on occupation. The sample in column (3) is based on the main sample, but the matching of treatment and control workers is done on propensity scores based on occupation and age, as opposed to exact matching on occupation. Workers in all samples are technicians and trade workers. Robust standard errors, clustered at the individual level are in parentheses. Controls include individual fixed effects and year fixed effects. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table .D.4: Estimated effects on health outcomes

	By skill		By skill and age			
	Higher skilled	Lower skilled	Higher skilled		Lower skilled	
			24-39 years	40-55 years	24-39 years	40-55 years
	(1)	(2)	(3)	(4)	(5)	(6)
A Psychological therapy service use						
2012/13	-0.003	0.000	0.004	0.000	0.005	0.000
	(0.007)	(0.006)	(0.027)	(0.007)	(0.019)	(0.006)
2013/14	-0.002	-0.008	0.006	-0.001	-0.006	-0.011*
	(0.008)	(0.006)	(0.027)	(0.008)	(0.021)	(0.007)
2014/15	0.008	0.001	0.022	0.004	0.021	-0.003
	(0.008)	(0.006)	(0.029)	(0.008)	(0.020)	(0.006)
2015/16	0.015*	-0.014**	0.037	0.012	-0.022	-0.009
	(0.009)	(0.007)	(0.032)	(0.008)	(0.021)	(0.007)
2016/17	0.002	-0.004	0.018	0.002	0.003	-0.005
	(0.009)	(0.006)	(0.031)	(0.009)	(0.021)	(0.007)
2017/18	0.007	-0.007	0.03	0.002	0.004	-0.009
	(0.008)	(0.007)	(0.030)	(0.008)	(0.022)	(0.007)
2018/19	0.006	-0.011	0.014	0.008	-0.014	-0.007
	(0.008)	(0.007)	(0.029)	(0.008)	(0.021)	(0.007)
2019/20	-0.007	-0.003	0.001	-0.002	0.015	-0.005
	(0.008)	(0.007)	(0.030)	(0.008)	(0.022)	(0.007)
2020/21	0.004	-0.004	0.031	0.000	-0.008	-0.003
	(0.008)	(0.006)	(0.030)	(0.008)	(0.020)	(0.006)
2021/22	-0.009	-0.001	-0.005	-0.007	0.019	-0.004
	(0.008)	(0.006)	(0.029)	(0.007)	(0.019)	(0.006)
2022/23	-0.002	0.000	0.028	-0.009	0.002	0.001
	(0.007)	(0.006)	(0.029)	(0.007)	(0.019)	(0.006)
Observations	40,460	68,590	9,620	30,830	14,990	53,600
B: Mental health medication use						
2012/13	0.013	0.010	0.038	0.009	0.059**	-0.006
	(0.011)	(0.009)	(0.040)	(0.010)	(0.028)	(0.009)
2013/14	0.018	0.000	0.036	0.016	0.011	-0.006
	(0.011)	(0.009)	(0.042)	(0.010)	(0.031)	(0.010)
2014/15	0.019*	0.000	0.015	0.022**	0.052*	-0.016*
	(0.011)	(0.009)	(0.041)	(0.011)	(0.031)	(0.010)
2015/16	0.020*	-0.007	0.066	0.013	0.002	-0.017*
	(0.012)	(0.010)	(0.044)	(0.012)	(0.030)	(0.010)
2016/17	0.018	-0.007	0.036	0.022*	0.009	-0.014
	(0.012)	(0.010)	(0.043)	(0.012)	(0.031)	(0.010)
2017/18	0.009	-0.024**	0.026	0.015	0.003	-0.031***
	(0.012)	(0.010)	(0.043)	(0.012)	(0.031)	(0.010)
2018/19	0.023**	-0.022**	0.032	0.019*	0.012	-0.033***
	(0.012)	(0.010)	(0.041)	(0.011)	(0.031)	(0.010)
2019/20	0.007	-0.026**	0.002	0.015	-0.008	-0.032***
	(0.012)	(0.010)	(0.044)	(0.011)	(0.031)	(0.011)
2020/21	0.015	-0.027***	0.044	0.005	-0.006	-0.032***
	(0.012)	(0.010)	(0.045)	(0.012)	(0.032)	(0.010)
2021/22	-0.012	-0.038***	-0.008	-0.010	-0.014	-0.046***
	(0.012)	(0.010)	(0.044)	(0.012)	(0.031)	(0.011)
2022/23	-0.004	-0.032***	-0.024	0.001	0.034	-0.044***
	(0.012)	(0.010)	(0.045)	(0.011)	(0.032)	(0.010)
Observations	40,500	68,640	9,620	30,880	14,980	53,660

Notes: The coefficients (time dummies interacted with treatment status) are compared to 2011/12, the first year of the sample, for automotive vis-à-vis construction and non-automotive manufacturing industry workers. Columns (1) and (2) present estimates differentiated by skill level: higher skilled refers to technicians and trade workers and lower skilled refers to machinery operators and drivers and labourers. Columns (3)-(6) present estimates differentiated by skill and age in 2011. Robust standard errors, clustered at the individual level are in parentheses. Controls include individual fixed effects and year fixed effects. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Figure .D.1: Estimated effects on health outcomes conditional on positive GP visits



Notes: These graphs are coefficient plots of the DiD event study estimates. The sample is restricted to individuals who have visited a GP at least once. Higher skilled refers to technicians and trade workers and lower skilled refers to machinery operators and drivers and labourers. The vertical spikes represent the 95% confidence interval for each coefficient. The vertical dashed lines indicate when the plant closure announcements were made and when plant operations started ceasing.