Motu Working Paper 26/05

Uneven vaccine uptake across industries

Motu economic & public policy research

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March 2026

Document information

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Acknowledgements
This research and two companion papers were completed while Richard was Chief Researcher at the New Zealand Royal Commission on Covid-19 Lessons Learned (part two). The analysis presented and conclusions drawn are his alone and do not reflect the views of the Royal Commission. Richard thanks Dave Maré (Motu Senior Fellow) for insightful feedback throughout the project and Motu Research for hosting him in their Datalab.

Disclaimer
These results are not official statistics. They have been created for research purposes from the Integrated Data Infrastructure (IDI) which is carefully managed by Stats NZ. For more information about the IDI please visit https://www.stats.govt.nz/integrated-data/. The results are based in part on tax data supplied by Inland Revenue to Stats NZ under the Tax Administration Act 1994 for statistical purposes. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the data's ability to support Inland Revenue's core operational requirements. Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Data and Statistics Act 2022. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

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 ISSN 1176-2667 (Print), ISSN 1177-9047 (Online).

Abstract

Somewhat counterintuitively, workers in the industries most affected by Covid-19 were slower to get vaccinated than workers in the least affected industries. We explain this raw correlation in terms of differences in worker characteristics. On average, less affected industry workers are more qualified and are more likely to have a history of influenza vaccination. Both these characteristics are strongly associated with early vaccine adoption. Worker sorting suggests that employers could be recruited to help close gaps in vaccination rates among hard-to-reach subpopulations.

JEL codes

D22 – firm behaviour: empirical analysis; H25 – business taxes and subsidies; I18 – government policy, regulation, public health

Keywords

Covid-19; vaccination rate; firms; workers; heterogeneity

Summary haiku

Vaccine adoption

slow in worst hit industries?

Duh! It’s the workers

1 Motivation

Covid-19 vaccination began in New Zealand on 19 February 2021 starting with vaccinators, border agents, and quarantine facility workers.[1] In three further tranches vaccination was made available to: health care workers (26 March); all individuals aged 65+ (17 May); and the general population (28 July) in age groups from older to younger. By 1 September 2021, a first dose of Covid-19 vaccine was available to all individuals in the working age population (18-64).

The vaccine was timely as New Zealand had adopted an elimination strategy that was predicated on the eventual development of an effective vaccine. Successful elimination is a double-edged sword – preventing outbreaks (saving lives), but also delaying the protection that comes from surviving the virus.

The elimination strategy included nationwide and regional lockdowns – restrictions on movement and work – that had a heterogeneous and material impact on New Zealand firm performance (Fabling 2026a). Counterintuitively, the industries most affected by Covid-19 – based on initial government wage support – experienced slower uptake of the first dose of the vaccine in their workforce compared to the least affected industries.[2] These differences in uptake are non-trivial. For example, in September 2021, when all workers had access to vaccination, the vaccination rate was almost 83% for professional services workers, but only 64% for construction workers. Since these industries each employ around 150,000 workers, achieving the superior professional services vaccination rate in the construction industry would have resulted in over 28,000 additional early vaccinated workers. Earlier vaccination may have averted ongoing restrictions on New Zealanders lives used to maintain the elimination strategy. In reality, it takes another 40 days before the construction industry reaches an 83% vaccination rate.

We describe the basic relationship between the relative severity of Covid-19 and related events on firms and vaccine uptake of workers in those firms, and then relate these patterns to workforce differences across industries using both simple univariate summary statistics and estimated multivariate hazard models. Aside from worker characteristics, we also control for other firm characteristics including firm size and the presence of working proprietors, as well as indicators for Covid-19 exposure – either directly or through co-workers.

Section 2 outlines the data and methods that we use. Section 3 reports estimates of the firm and worker characteristics associated with early vaccine uptake, while section 4 summarises findings.

[1] Vaccination roll-out dates are provided by DPMC (2023).

[2] The proportion of first-dosed individuals receiving subsequent booster shots is very high, so we focus exclusively on initial vaccination patterns.

2 Data & method

2.1 Data

We use New Zealand's Integrated Data Infrastructure (IDI) and related user-generated tables to estimate the vaccine uptake rate across different worker and firm subgroups. Fabling-Maré's labour tables identify employer-employee relationships, monthly earnings, job spells and two-way worker (WFE) and firm (FFE) log wage fixed effects (Fabling and Maré 2015).[3] These data cover our full population of interest – 18-64 year olds employed (paid a wage or salary) in February 2021. We drop workers whose job is starting or ending in that month, which removes "short-spell" (one to two month) jobs and ensures that workers are somewhat attached to their employers industry. For the same reason, we focus on an employees main (highest earning) job in the month and derive firm characteristics solely from that employer.

Data availability restrictions are minor because of the broad coverage of administrative and Census data included in the IDI, the restriction to individuals who are well connected to the New Zealand labour market, and the use of imputed values from the Fabling-Maré characteristics table. For our analysis, workers must have observed sex, birth month, ethnicity, country of birth, highest qualification and residential address, and their employer must have an industry and private-for-profit status. Highest qualification, country of birth and year of arrival to live in New Zealand combine various sources, including five-yearly Census.[4] Cleaned residential meshblock location for the labour table population (Fabling and Maré 2020) is mapped to Regional Council.

Covid-19 vaccination and testing data are provided by the Ministry of Health, and identify the day of vaccination, and of reported positive or negative test result.[5] We also draw on influenza vaccination data from the same source, which identifies workers who have a history of vaccination over 2018-2020. We require each worker to be linked to the Ministry of Health dataset in the IDI. This restriction does not require workers to have been vaccinated or tested but, rather, means that any Covid-19 data an individual has is linked to their employment history and other data in the IDI. Linking to employer-employee data means we can construct indicators for whether a worker has been "exposed" to Covid-19 via the workplace, meaning that they may have encountered a co-worker who has had Covid-19 and/or who has been vaccinated.

Employer Covid Wage Subsidy (CWS) data is linked within the IDI to firms using confidentialised Inland Revenue numbers. The CWS was paid to firms during lockdowns to enable them to re-

[3] Maré and Fabling (2025) describe subsequent improvements to worker and firm fixed effect estimation, including restricting the estimation sample to main jobs, consistent with our analysis.

[4] These characteristics and others, including Māori descent, are included in a new employee and working proprietor table on IDI_Adhoc (described in Appendix A). Labour tables are updated annually by the author, and available to all authorised users of the IDI IR schema via secure Datalab access. Birth month and level one ethnicity data come from Stats NZ's personal details table on the IDI. We use the 202410 instance, which is the latest available at the time of analysis.

[5] For the timeframe we consider, most tests are self-administered and voluntarily self-reported.

tain workers in cases where the impact of Covid-19 and associated events was substantial.[6] We use these data to identify cross-industry variation in the impact of the pandemic and related events, including lockdowns, border closures and disruptions to global trade. Only CWS payments received prior to the vaccine roll-out are used to avoid potential reverse-causality – ie, firms requiring government support because their workers are unvaccinated.

The speed of vaccination in some sectors is directly influenced by government policy, either through directives (government departments), priority access (health workers), or vaccine mandates (particularly health and education, see Fabling 2026b). We include public sector jobs in the analysis for the purpose of comprehensively describing vaccination patterns across workers, but exclude their industries from the analysis of the relationship between the impact of Covid-19 on business and vaccine uptake.

Other firm characteristics included in the analysis are: firm size (the log to total firm full-time equivalent (FTE) employment); private-for-profit status; and whether the firm has working proprietors (WPs). These controls help ensure that other relationships are robust to cross-industry variation in firm characteristics. In particular, firm size controls for the statistical relationship between co-worker exposure and number of co-workers.

In summary, the unit of observation is almost 1.8 million workers in a mid-spell job as at February 2021. The analysis period is 19 February 2021 through to 31 January 2022, with graphical summaries focussing on the period from 25 March to 30 December 2021, during which the majority of workers receive a first vaccination.

2.2 Method

What follows is a survival analysis, where we estimate Cox proportional hazard models to establish the relationship between vaccination and worker and firm characteristics in a multivariate setting. In this context, "failure" is the positive outcome of vaccination, and the vaccination rate is the corresponding failure function. The hazard rate at any given date – which underlies the estimation approach – is the probability of becoming vaccinated in the following day, given that the worker is not already vaccinated (ie, is still in the "at risk" population).

In the survival analysis workers leave the population at the point where they become vaccinated, die or leave New Zealand for at least a month.[7] Workers who are not vaccinated by the final analysis day (31 January 2022) are right-censored and the hazard model accounts for this censoring. The first three rows of table 1 show the proportion of workers that exit the population, are vaccinated and are right-censored with those three groups covering all 1,795,131 workers. Less than one percent of workers leave the population with deaths combined with outward migration for confidentiality reasons. Exiting is most common for Pacific, Asian and

[6] See Hyslop et al. (2023) for an evaluation of the CWS and discussion of the related data.
[7] We choose to exclude returnees, in part because of their uncertain vaccination status.

Middle Eastern, Latin American and African (MELAA) ethnicity workers.[8] Almost 94% of the population has a first vaccination by 31 January 2022, with women being one percentage point (pp) more likely to be vaccinated than men. Māori (Asian) ethnicity workers are most (least) likely to be unvaccinated (right-censored).

Figure 1(A) shows how the vaccination rate develops over time for the full population of workers. Vertical grey lines highlight key dates in the vaccination programme. The first four lines reflect the roll-out to health workers; over 65s; and the start and end of the staggered roll-out to all individuals by age groups. The fifth and sixth lines denote other policy decisions that appear to have had a noticeable impact on vaccination, specifically the "Super Saturday" vaccination drive (16-Oct) and the introduction of vaccine passes that restricted access to locations for the unvaccinated (17-Nov). The potential effect of these policies is easiest to observe in figure 1(B), which shows the associated hazard rate. From here it is apparent that the probability of vaccination (for the not-yet-vaccinated) accelerated when vaccination was opened the the general population (between 28-Jul and 1-Sept), and again for Super Saturday and the introduction of vaccine passes.[9] Ultimately, because the population of unvaccinated eventually only include workers who choose not to be vaccinated (or cannot be for health reasons, for example) the hazard rate must fall over time, declining to near zero by the end of 2021.

In a survival analysis with no time-varying characteristics, each worker can be represented by a single spell that ends with exit, survival or failure. Aside from residential location, worker characteristics are time-invariant (or assumed so over the year analysed), but job characteristics change when workers move employers.[10] Covid-19 exposure variables are also time-varying. To accommodate these changes, spells are split whenever a time-varying characteristic changes.

Table 1 shows the proportion of workers who ever move region or change employer, including transitions into not employed. Over the analysis period, three percent of workers move Regional Council at least once, while 9% have at least one spell of not having a job and 14% change employer at some point. When workers change employer, there is a 64% probability of at least one of those job changes being to a different industry division, implying some persistence in worker industry, but not overwhelmingly strong. However, because most workers do not change employer during the year, 91% of workers have a consistent industry division throughout the analysis.

[8] Ethnicity is multiple response and workers are included in each applicable group. "Other" ethnicity is classified as "European" based on Census analysis.

[9] The Super Saturday peak doesn't align exactly with the date of the event because the hazard rate uses the (smoothed) five-day frequency of panel (A), rather than the daily frequency of the dataset.

[10] Firm size is constant using FTE at February 2021 (initial job) or the month a worker joins a new firm.

3 Results

3.1 Vaccination rate over time

Figures 2-4 and table 2 summarise the key facts that we seek to explain. Firstly, the four panels of figure 2 report the vaccination rate over time for each of the 19 industry divisions plus workers not in a job. Panel (A) contains the industries with the lowest vaccination rates as at 21 September 2021 and panel (D) contains the industries with the highest vaccination rates (at the same date). This date is three weeks after vaccination becomes unrestricted, and is the date with the greatest variation in rates across private sector industries. The top left column of table 2 reports vaccination rates by industry at this date, also ordered from lowest to highest. Compared to the overall vaccination rate of 75%, agriculture, forestry & fishing has a rate of 55%, while professional, scientific & technical services has a rate of 83%. Including public sector dominated industries (divisions O, P & Q), the range of vaccination rates is almost 33pp.

Figure 3 shows an alternative way to express the private sector cross-industry variation. To generate the solid line, we first rank each detailed (three-digit) industry by the proportion of workers that are in firms that received the CWS prior to vaccination becoming available and then classify industries into low, moderate and high (LMH) impact groups based on the CWS rate so that approximately a third of workers are included in each group. The line plots the difference between the vaccination rate for workers in the low (CWS) impact and the high (CWS) impact groups. This difference peaks after vaccination becomes available to all workers and the difference is about 8pp indicating that workers in industries that were less affected by Covid-19 were likely to get vaccinated sooner than workers in more affected industries. The dotted line groups workers based on whether their own employer previously received the CWS. While the difference peaks at about half the level of the low-high impact comparison, the timing is identical and supports the view that less affected firms experienced faster vaccination of their workers.

Figure 4 plots the variation in uptake at the division level against the proportion of workers in firms receiving the CWS (our metric for how affected the industry is). The correlation between the two rates is -0.586. Differences in worker characteristics are likely to explain at least some of the observed negative correlation and the remainder of table 2 reports 21 September vaccination rates by sex, age, New Zealand-born, ethnicity, highest qualification, Regional Council and prior influenza vaccination. Aside from sex and NZ-born, each characteristic reveals substantial heterogeneity in the speed of uptake. Some of these differences likely reflect prioritisation of the roll-out, particularly the gap between old (51-64) and young (18-29), and the gap between women and men. The genesis of these two gaps can be seen in figure 5 where the sex-based gap develops during the prioritisation of the female-dominated health sector, and figure 6 where the age-based gap is established during the prioritisation of older individuals.

Other gaps, though, are substantial and not as easily explained by prioritisation. The variation across ethnicities (26pp) is consistent with the pattern of vaccination/non-vaccination reported

in table 1. September vaccination rates are strictly increasing in highest qualification with a gap of 23pp between post-graduates (88%) and those with no formal qualifications (65%). Across regions, Taranaki (63%) and Auckland (82%) bookend the range of vaccination rates (19pp).

The evolution of vaccination rates for workers with these characteristics is captured in figures 7-9. For location, in particular, there is strong variation in these paths with some regions, such as the West Coast (panel A) initially having relatively high vaccination rates before falling into the lowest regional grouping by 21 September. Canterbury (panel B) accelerates away from other regions in it's grouping to have one of the highest vaccination rates by year end, while Nelson (panel D) falls away from other member of the highest adoption group after 21 September.

The subgroup with the highest vaccination rate at 21 September (90%) is those who have received at least one influenza vaccination over 2018-2020. This correlation is likely driven by a mix of willingness to receive vaccines, sorting of at-risk individuals into the group and, potentially, a relationship between healthcare access, cost, income and education. Figure 10 suggest that the health sector and age-related risk factors are relevant with the gap between flu vaccinators and non-vaccinators opening up during the early phases of the Covid-19 vaccine roll-out.

3.2 Worker sorting across industries

The presence of strong variation in vaccination rates across worker characteristics presents only half of the picture necessary to explain the observed industry-level variation. We also need workers to sort into industries in a systematic way that reinforces the aggregate patterns. Table 3 presents these corroborating statistics by industry division.[11] Focussing on the bottom panel where firms are sorted into LMH impact industries (as in figure 3) plus public sector dominant divisions, the strongest difference across groups is the variation in graduate or higher qualifications (final column). Around 42% of workers in low Covid-19 impact industries have a degree, compared to 23% in high impact industries. Additionally, in high impact industries, Māori and Pacific ethnicity workers are overrepresented, and the average worker is three years younger than the overall mean. All these factors are consistent with slower uptake of Covid-19 vaccination in high impact industries due to worker differences.

Table 4 summarises firm characteristics by industry. Statistics are averaged over workers, with the first column reporting the number of workers in the industry in February 2021. Arithmetic means are used except firm size (FTE) and monthly FTE wages (W) which are geometric means, reflecting the use of these variables in subsequent models (ie, as log firm size, WFE and FFE). Mean firm size varies over two orders of magnitude from 12 FTE for other services and agriculture, forestry & fishing to almost 2,500 FTE for public administration & safety. Firms are smaller in high impact industries (mean 37 FTE) than in low impact industries (148 FTE). Mean worker fixed effects (WFE) are consistent with the qualifications statistics in table 3 with high impact industries eight log points lower than low impact industries. Mean firm fixed effects (FFE) are

[11] For simplicity, mean worker and firm summary statistics are presented using characteristics at the start of the analysis period (February 2021) when all workers are employed.

consistent with positive sorting between high (low)-paid workers and high (low)-paying firms, with the industry-level correlation between mean WFE and mean FFE of 0.723, and the mean FFE for high impact industries is 13 log points lower than low impact industries. Together these differences result in mean W being $1,436 higher in low impact industries over high impact industries. High impact industries are 53pp more likely to have working proprietors than low impact industries, consistent with the smaller average size of the former group.

As expected, there is a substantial gap in private-for-profit (PFP) status between public sector dominated industries and other industries. PFP businesses in the former are concentrated in health care & social assistance, with aged care being a primarily for-profit sub-industry. The final column of table 4 reports the proportion of workers in firms receiving the CWS prior to the vaccine roll-out (used in figure 4). By design, this rate is increasing by impact group and lowest for public sector dominant industries. Even so, 24% of low impact industry workers are in firms previously receiving the CWS.

We favour the industry and LMH grouping to classify the impact of Covid-19 as these mitigate the risk of the analysis being affected by unobservables associated with specific firms receiving the CWS. Of the two industry groupings, the LMH impact approach is better for formal testing and is a more nuanced allocation of impacted industries (three-digit vs division). The industry approach is better for illustrative purposes, identifying industries, and as a way to control for other cross-industry differences.

3.3 Hazard models – worker characteristics

We initially report estimated Cox proportional hazard models with worker characteristics separately and together (table 5 and figures 11 and 12). While these coefficients are not the primary focus of the paper, public health policy focussed on vaccination rates by worker characteristics. Given the targeted delivery based on age and ethnicity, we include sex, age and ethnicity in all specifications starting with column (1) which includes only these variables.[12] Subsequent columns individually introduce indicators for recent and long-term migrant (column 2);[13] country of birth (column 3 and figure 11(A)); highest qualification (column 4); worker fixed effects (column 5); Regional Council (column 6 and figure 12); and prior influenza vaccination in each of the three prior calendar years (column 7). The final column of table 5 includes all worker characteristics with separate country of birth coefficients estimated for recent and long-term migrants (figure 11(B)). In the case of coefficients reported in figures, these include 95% confidence intervals and are ordered by estimated coefficient in the variable-specific model.

Estimated coefficients represent a multiplicative scaling of the estimated base hazard function with no covariates. Thus a coefficient is greater than one when a variable is associated with

[12] Unreported tests with year-specific indicator variables for age suggest that a linear specification for age is appropriate. There is no omitted category for ethnicity because it is multi-response. Omitted categories for other variables are listed in the table note.

[13] Long-term migrants arrived to live in New Zealand prior to 2009.

earlier vaccination (a higher hazard rate) and less than one for variables associated with later vaccination or non-vaccination (a lower hazard rate).

Coefficients in columns (1)-(7) correspond strongly to the rankings reported in table 2 of vaccination rates at 21 September 2021. To avoid repetition, we focus on comparing (8) with earlier columns, which provides context for cross-group variation in vaccination uptake rates. Key modulating factors include educational attainment (for ethnicity-based variation), prior flu vaccination (for sex) and location (for some ethnicities). Regions with large cities – particularly Wellington – have a higher proportion of graduates, which explains a non-trivial share of the cross-region variation in vaccination rates (gap between estimates in figure 12).

MELAA is the smallest ethnicity group and geographically diverse. The inclusion of country of birth indicators affects the MELAA ethnicity coefficient with South & Central American, North African and Middle Eastern-born workers among the highest point estimates (figure 11(A)). Aside from Pacific, other ethnicity coefficients are largely unaffected by the inclusion of country of birth. Figure 11(B) confirms that recent migrants have higher point estimates than long-term migrants across the majority of birth countries, consistent with the estimates from column 2 of table 5.

Coefficients on graduate, post-graduate and WFE are lower – but still significantly greater than one – when qualification and wage premium are both included (column 8), compared to separately (columns 4 and 5). Clearly, neither metric is a complete measure of worker ability and both variables suggest higher ability individuals are more likely to be vaccinated early. In terms of model fit (χ^2), prior flu vaccination has the greatest explanatory power, with both more recent and more frequent vaccination associated with earlier Covid-19 vaccination.[14]

3.4 Hazard models – industry

Table 6 reports division-based industry findings, introducing worker characteristics (column 2), followed by firm characteristics (column 3) and then Covid-19 exposure variables (column 4).[15] Figure 13 recasts the motivating industry impact (CWS rate) correlation in four panels (A)-(D) corresponding to non-public sector dominated industry coefficients from columns (1)-(4). The no covariates (panel A) correlation is -0.530, which is similar to the raw correlation in figure 4 based on 21 September vaccination rates (-0.586). Introducing worker characteristics (panel B) explains a substantial proportion of cross-industry variation (reducing the standard deviation of industry coefficients from 0.188 to 0.113), and the correlation with CWS uptake-based impact to -0.328. The addition of firm characteristics and exposure variables results in a positive correlation of 0.112 and 0.172 respectively. That is, once we control for worker and firm characteristics, the association between the impact of Covid-19 and related events and the speed

[14] See Fabling (2026b) for related statistics in the context of vaccine mandate defiance.

[15] The omitted industry category is not in a job, meaning that – aside from agriculture, forestry & fishing, and mining – industry point estimates always exceed one.

at which workers become vaccinated is reversed – with more affected industries vaccinating faster.

An alternative way to see this transition is to use the LMH impact classification of three-digit industries and repeat the exercise of adding blocks of covariates (top panel of table 7). Column (1) shows that – in the absence of other covariates – low impact industries have a higher coefficient than high impact industries, with moderate impact industries between the two. This approach enables formal statistical tests of group coefficient equivalence and the relevant p-values are reported below the χ^2. In the no covariates model, LMH impact coefficients are significantly different from each other at the 0.1% level. Adding worker characteristics (column 2) brings all three point estimates within 0.02 of each other, though still significantly different (at the 5% level). Consistent with figure 13, high impact industries have a (significantly) higher coefficient than low impact industries once we additionally control for firm characteristics (column 3) and Covid-19 exposure (column 4) with moderate impact industry coefficients between these estimates.

The bottom panel of table 7 shows estimates with separate coefficients for CWS recipient and non-recipient firms in non public sector dominant industries, and shows the same pattern as the industry and LMH grouping approaches. As in the upper panel of the table, coefficients are closest to being equal in the specification that only includes worker characteristics, though still significantly different from each other (at the 5% level).

For completeness, tables 8-10 report coefficients on worker, firm and Covid-19 exposure variables in the presence of all variables (ie, the remaining estimates from the "all" specifications in tables 6 and 7). Estimated coefficients are consistent across the three firm groupings – industry division, LMH impact and CWS recipient/non-recipient. Comparing table 8 with the all worker characteristics specification (table 5, column 8), the obvious first difference is that women are now estimated to be slightly less likely to be vaccinated early than men after controlling for firm characteristics – coefficient of 0.98-0.99 compared to 1.09. This reversal follows from the dominance of women in the education and health sectors (table 3) and the relatively high vaccination rates in those industries. The largest absolute shift in ethnicity coefficients is for Pacific workers (from 0.92 to 0.87). The gradient in highest qualification coefficients is reduced substantially with the coefficient for post-graduate changing from 1.31 to 1.17-1.18, offset by an increase of the WFE coefficient (from 1.38 to 1.42-1.43). This shift reflects the positive sorting of skilled workers into low impact industries and high FFE firms (which is now directly controlled for). Finally, in terms of coefficients common to both table 5 and 8, the flu vaccine gradient also reduces slightly, speculatively reflecting systematic differences in free employee influenza vaccination programmes, particularly between the public, private and not-for-profit sectors.

The Regional Council coefficient estimates in table 9 are comparable to coefficients plotted in figure 12 and suggest that the main effect of controlling for firm and Covid-19 exposure differences is to explain some of Nelson, Wellington and Auckland's superior vaccination uptake – with remaining coefficients increasing by between 0.05 and 0.10 relative to those three regions.

Finally table 10 reports estimates for variables not included in the worker characteristics spec-

ifications. Firm controls are primarily included to remove alternative interpretations of other variables, particularly the mechanical relationship between firm size and the potential for co-worker exposure. Given the presence of a firm size wage premium, we do not interpret the slightly lower than one coefficient on firm size as meaningful in the presence of a strong positive coefficient on the FFE variable. Similarly, the presence of working proprietors is negatively correlated with firm size and only weakly positively linked to vaccination in one of the three specifications. Despite direct controls for public sector dominated industries – workers in private-for-profit firms are additionally less likely to vaccinate early (coefficient of 0.88) compared to the not-for-profit sector.

Compared to firm characteristics, exposure variables add substantially to the model goodness-of-fit (comparing χ^2 across columns in table 6). Workers who have had Covid-19 are more likely to get vaccinated afterwards (coefficient of 1.11), but not if they are within the post-infection period where they are prohibited from being vaccinated (coefficient of 0.89, significantly different from zero at the 5% level in two out of the three specifications). Having had a vaccinated co-worker is consistent with a strong demonstration effect (coefficient 1.75-1.76), controlling for firm size and industry. Because of worker sorting, it is possible that this variable captures a similarity in vaccination propensity across co-workers, though the direct controls for worker characteristics should partially control for that possibility. Finally, prior co-worker exposure to Covid-19 is also positively linked to vaccination, which could reflect greater salience of the consequences of the virus or a perceived greater need for protection.

4 Conclusions

The urgency with which workers get vaccinated differs substantially by industry, with industries most affected by Covid-19 experiencing slower uptake than least affected industries. Estimates from multivariate hazard models imply that this industry-level correlation is largely due to differences in worker characteristics, particularly qualifications and prior vaccination history. Results are robust across three different specifications of industry groups. In particular, low-moderate-high impact industry grouping estimates suggest that vaccination uptake is almost the same across groups controlling for worker characteristics. In the additional presence of firm characteristics, high impact industries are estimated to have faster vaccine uptake than low impact industries – ie, the reverse of the raw relationship.

Employer incentives are aligned, therefore, with closing gaps in broad, rapid uptake across the working population. That is, hard-to-vaccinate individuals are concentrated in firms that are the worst affected by the pandemic. These firms are the most likely recipients of the Covid Wage Subsidy and, potentially, have the most to gain from regional vaccination rates being high enough to avoid restrictions on business. Recruiting firms to encourage uptake in less-vaccinated groups is a policy lever that could be considered in future.[16]

[16]Firm-specific vaccine mandates became possible, but the official "vaccination assessment tool" to aid firm decisions on this was released on 15 December 2021 (94% of workers already vaccinated).

While it is easy to credit the relationship between qualifications and vaccination speed to attitudes towards science and/or susceptibility to misinformation, it is likely that these results are related to uneven access to and connection with the healthcare system for low income individuals. One way private-sector firms could encourage workers to get vaccinated in future pandemics might be through the normalisation of annual influenza vaccination, increasing the reach of these programmes through subsidised or free shots, as is common in the public sector.

While far from a formal evaluation, vaccine passes appear to have impacted vaccination decisions for the slowest adopters (figure 1(B), final vertical line). A key question for future pandemics is whether more can be achieved with the carrot (eg, nudging preferences), rather than the stick (mandates and restrictions).

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Tables

Table 1: Proportion of workers changing characteristics by sex and ethnicity

	Proportion of workers							
	Overall	Female	Male	European	Māori	Pacific	Asian	MELAA
Leaves population	0.009	0.008	0.011	0.008	0.006	0.014	0.014	0.020
Vaccinated	0.939	0.944	0.934	0.936	0.908	0.929	0.965	0.932
Not vaccinated	0.052	0.048	0.055	0.057	0.086	0.057	0.021	0.048
Moves Regional Council	0.033	0.030	0.035	0.032	0.042	0.025	0.034	0.044
Not in a job	0.088	0.096	0.081	0.084	0.130	0.109	0.080	0.110
Changes main employer	0.139	0.137	0.141	0.129	0.165	0.158	0.157	0.189
Changes industry (division)	0.089	0.090	0.088	0.083	0.109	0.108	0.096	0.121
Conditional on new employer	0.641	0.660	0.623	0.644	0.663	0.684	0.615	0.639
N(workers)	1,795,131	875,430	919,701	1,214,574	259,704	139,770	349,482	35,889

Workers leave the population prior to vaccination if they die or if they leave New Zealand for at least one month. These outcomes are pooled because they are dominated by outward migration. Not vaccinated means first dose has not been administered by the end of the analysis period (31 January 2022).

Table 2: Vaccination rate at 21 September 2021 by worker and firm characteristics

	Characteristic	Rate	Characteristic	Rate
	All workers	0.754	Ethnicity	
	Industry		Māori	0.601
A	Agriculture, Forestry & Fishing	0.551	Pacific	0.670
	Not in a job	0.608	European	0.746
E	Construction	0.642	MELAA	0.760
B	Mining	0.662	Asian	0.861
S	Other Services	0.696	**Range**	**0.260**
H	Accommodation & Food Services	0.702	Highest qualification	
N	Administrative & Support Services	0.710	None	0.646
C	Manufacturing	0.715	School	0.678
G	Retail Trade	0.740	Post-school	0.710
I	Transport, Postal & Warehousing	0.750	Graduate	0.826
L	Rental, Hiring & Real Estate Services	0.757	Post-graduate	0.881
R	Arts & Recreation Services	0.763	**Range**	**0.235**
F	Wholesale Trade	0.767	Regional Council	
D	Electricity, Gas, Water & Waste Services	0.776	Taranaki	0.630
P	Education & Training	0.811	Bay of Plenty	0.641
K	Financial & Insurance Services	0.825	Northland	0.645
M	Professional, Scientific & Technical Services	0.828	West Coast	0.661
J	Information Media & Telecommunications	0.832	Gisborne	0.670
O	Public Administration & Safety	0.851	Southland	0.682
Q	Health Care & Social Assistance	0.877	Tasman	0.701
	Range	**0.326**	Canterbury	0.702
	Sex		Manawatū-Whanganui	0.704
	Male	0.727	Waikato	0.704
	Female	0.781	Hawke's Bay	0.714
	Range	**0.054**	Marlborough	0.755
	Age group		Nelson	0.759
	Young	0.636	Otago	0.799
	Middle-aged	0.755	Wellington	0.805
	Old	0.857	Auckland	0.822
	Range	**0.221**	**Range**	**0.193**
	New Zealand-born		Prior influenza vaccination	
	Yes	0.716	No	0.713
	No	0.821	Yes	0.901
	Range	**0.106**	**Range**	**0.188**

The standard deviation of vaccination rates across industries (excluding O, P, Q and not in a job) peaks on 21 September 2021, three weeks following unrestricted vaccine access. Ethnicity is multiple response ("Other" ethnicity grouped with European). Age groups are: young (18-29); middle-aged (30-50); old (51-64). Prior influenza vaccination is any of the three prior calendar years (2018-2020).

Table 3: Mean worker characteristics by industry

			Mean		Proportion					
		N	Age	Female	European	Māori	Pacific	Asian	MELAA	Grad+
A	Agriculture, Forestry & Fishing	74,649	37.8	0.301	0.663	0.209	0.070	0.152	0.021	0.173
B	Mining	4,530	43.8	0.175	0.829	0.187	0.030	0.054	0.012	0.246
C	Manufacturing	201,885	41.6	0.308	0.624	0.167	0.115	0.186	0.018	0.239
D	Electricity, Gas, Water & Waste Services	17,859	43.0	0.316	0.717	0.161	0.076	0.149	0.017	0.380
E	Construction	153,822	38.0	0.138	0.706	0.181	0.079	0.150	0.019	0.166
F	Wholesale Trade	90,069	41.6	0.357	0.706	0.107	0.089	0.181	0.017	0.300
G	Retail Trade	169,239	36.4	0.551	0.665	0.130	0.065	0.243	0.018	0.278
H	Accommodation & Food Services	107,412	32.7	0.591	0.508	0.135	0.060	0.382	0.033	0.282
I	Transport, Postal & Warehousing	72,732	42.8	0.280	0.634	0.184	0.133	0.162	0.013	0.214
J	Information Media & Telecommunications	22,986	39.6	0.415	0.693	0.088	0.049	0.247	0.022	0.581
K	Financial & Insurance Services	58,317	41.3	0.555	0.691	0.084	0.058	0.244	0.016	0.535
L	Rental, Hiring & Real Estate Services	26,781	41.2	0.522	0.729	0.125	0.068	0.168	0.018	0.363
M	Professional, Scientific & Technical Services	144,672	39.8	0.479	0.757	0.074	0.025	0.200	0.024	0.675
N	Administrative & Support Services	72,141	38.5	0.456	0.513	0.172	0.164	0.237	0.033	0.281
O	Public Administration & Safety	134,577	42.0	0.508	0.751	0.160	0.087	0.123	0.016	0.509
P	Education & Training	154,326	44.1	0.753	0.769	0.159	0.058	0.114	0.017	0.724
Q	Health Care & Social Assistance	201,861	43.6	0.821	0.648	0.132	0.070	0.231	0.020	0.587
R	Arts & Recreation Services	26,367	37.1	0.537	0.778	0.157	0.069	0.122	0.019	0.429
S	Other Services	60,891	40.4	0.516	0.717	0.148	0.069	0.167	0.020	0.294
	Total – public sector dominant (O, P, Q)	490,776	43.3	0.714	0.714	0.148	0.071	0.164	0.018	0.609
	– low impact	440,058	40.2	0.432	0.678	0.140	0.067	0.202	0.019	0.419
	– moderate impact	437,760	40.0	0.367	0.686	0.140	0.081	0.184	0.018	0.304
	– high impact	426,537	37.0	0.408	0.623	0.150	0.094	0.233	0.025	0.231
	– overall	**1,795,131**	**40.2**	**0.488**	**0.677**	**0.145**	**0.078**	**0.195**	**0.020**	**0.398**

Means of worker characteristics as at $t = 0$. Proportions by ethnicity do not sum to one because of multi-ethnicity workers. Subtotal classification based on Covid Wage Subsidy uptake at the three-digit industry level, with public sector dominant industry divisions separate.

Table 4: Mean firm characteristics by industry

			Mean			Proportion		
		N	FTE	W	FFE	WFE	PFP	WP	CWS
A	Agriculture, Forestry & Fishing	74,649	12	$ 5,021	-0.080	-0.069	0.943	0.421	0.557
B	Mining	4,530	108	$ 8,401	0.244	0.044	0.997	0.589	0.066
C	Manufacturing	201,885	121	$ 5,932	0.039	-0.064	0.990	0.658	0.235
D	Electricity, Gas, Water & Waste Services	17,859	317	$ 7,260	0.115	0.036	0.987	0.256	0.072
E	Construction	153,822	27	$ 5,768	-0.022	-0.013	0.994	0.756	0.490
F	Wholesale Trade	90,069	53	$ 6,105	0.014	-0.008	0.973	0.659	0.240
G	Retail Trade	169,239	106	$ 4,507	-0.106	-0.084	0.986	0.643	0.355
H	Accommodation & Food Services	107,412	17	$ 4,121	-0.146	-0.096	0.967	0.865	0.372
I	Transport, Postal & Warehousing	72,732	162	$ 6,017	0.042	-0.059	0.992	0.738	0.217
J	Information Media & Telecommunications	22,986	242	$ 7,142	0.114	0.058	0.971	0.316	0.247
K	Financial & Insurance Services	58,317	629	$ 7,728	0.173	0.094	0.899	0.178	0.049
L	Rental, Hiring & Real Estate Services	26,781	23	$ 5,840	-0.006	-0.003	0.948	0.654	0.248
M	Professional, Scientific & Technical Services	144,672	53	$ 7,088	0.061	0.103	0.904	0.497	0.331
N	Administrative & Support Services	72,141	93	$ 4,816	-0.070	-0.098	0.943	0.800	0.252
O	Public Administration & Safety	134,577	2,494	$ 6,704	0.092	0.024	0.100	0.085	0.032
P	Education & Training	154,326	109	$ 5,493	-0.074	0.033	0.159	0.199	0.047
Q	Health Care & Social Assistance	201,861	428	$ 5,452	-0.031	0.001	0.449	0.442	0.094
R	Arts & Recreation Services	26,367	52	$ 4,918	-0.091	-0.028	0.499	0.744	0.109
S	Other Services	60,891	12	$ 4,817	-0.126	-0.060	0.644	0.668	0.338
	Total – public sector dominant (O, P, Q)	490,776	452	$ 5,782	-0.011	0.017	0.262	0.268	0.062
	– low impact	440,058	148	$ 6,283	0.046	0.009	0.880	0.329	0.241
	– moderate impact	437,760	40	$ 5,662	-0.019	-0.029	0.977	0.722	0.338
	– high impact	426,537	37	$ 4,847	-0.079	-0.070	0.966	0.860	0.362
	– overall	**1,795,131**	**105**	**$ 5,630**	**-0.015**	**-0.017**	**0.755**	**0.534**	**0.244**

Firm characteristics ($t = 0$) averaged over workers. Geometric mean used for firm FTE and wage (W). FFE=firm fixed effect; WFE=worker fixed effect; PFP=private-for-profit; WP=firm with working proprietor(s); CWS=Covid Wage Subsidy recipient firm. Overall FFE and WFE are non-zero because fixed effects are estimated using FTE weights.

Table 5: Estimated hazard model coefficients – worker characteristics

	None	Migrant		Skill		RC	Flu	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	1.153**	1.154**	1.163**	1.104**	1.150**	1.148**	1.099**	1.093**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Age (base month)	1.019**	1.019**	1.019**	1.019**	1.020**	1.019**	1.017**	1.018**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
European	1.025**	1.047**	1.075**	1.013**	0.977**	1.035**	1.020**	1.039**
	[0.003]	[0.003]	[0.004]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Māori	0.790**	0.813**	0.821**	0.831**	0.811**	0.818**	0.801**	0.898**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Pacific	0.989**	0.988**	0.926**	1.049**	1.018**	0.918**	0.996	0.921**
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.003]	[0.004]	[0.004]
Asian	1.497**	1.437**	1.480**	1.370**	1.522**	1.423**	1.489**	1.315**
	[0.005]	[0.005]	[0.007]	[0.005]	[0.005]	[0.005]	[0.005]	[0.007]
MELAA	1.068**	1.026**	0.940**	0.996	1.088**	1.024**	1.085**	0.943**
	[0.007]	[0.006]	[0.009]	[0.006]	[0.007]	[0.006]	[0.007]	[0.009]
Recent migrant		1.103**						
		[0.003]						
Long-term migrant		1.078**						
		[0.003]						
HQ – None				0.834**				0.864**
				[0.003]				[0.004]
– Post-school				1.063**				1.053**
				[0.002]				[0.002]
– Graduate				1.314**				1.222**
				[0.003]				[0.003]
– Post-graduate				1.501**				1.314**
				[0.004]				[0.004]
WFE					1.702**			1.383**
					[0.006]			[0.005]
Flu vaccine – 2018							1.432**	1.393**
							[0.008]	[0.008]
– 2019							1.449**	1.407**
							[0.007]	[0.007]
– 2019 & 2018							1.662**	1.620**
							[0.014]	[0.014]
– 2020							1.776**	1.700**
							[0.005]	[0.005]
– 2020 & 2018							1.949**	1.885**
							[0.015]	[0.014]
– 2020 & 2019							2.060**	2.001**
							[0.012]	[0.012]
– All three							2.224**	2.226**
							[0.012]	[0.012]
Goodness-of-fit (χ^2)	126,755	130,394	142,269	154,283	142,050	143,658	206,697	284,925
CoB (3)/CoB×recency (8)	N	N	Y	N	N	N	N	Y
Regional Council	N	N	N	N	N	Y	N	Y
Multiple jobs	N	N	N	N	N	N	N	Y

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Omitted categories male and: NZ-born (2,3); HQ school (4); has WFE (5, indicator excluded); living in Auckland (6); no flu vaccination 2018-2020 (7). Ethnicity multi-response (no omitted category).

Table 6: Estimated hazard model coefficients – industry division

		None	Worker	Firm	All
		(1)	(2)	(3)	(4)
A	Agriculture, Forestry & Fishing	0.893**	0.995	1.074**	1.129**
		[0.004]	[0.005]	[0.007]	[0.008]
B	Mining	1.071**	1.047**	0.981	0.980
		[0.017]	[0.017]	[0.017]	[0.017]
C	Manufacturing	1.241**	1.220**	1.207**	1.201**
		[0.005]	[0.005]	[0.007]	[0.007]
D	Electricity, Gas, Water & Waste Services	1.414**	1.285**	1.219**	1.228**
		[0.011]	[0.011]	[0.012]	[0.012]
E	Construction	1.070**	1.115**	1.164**	1.190**
		[0.004]	[0.005]	[0.007]	[0.007]
F	Wholesale Trade	1.387**	1.275**	1.298**	1.308**
		[0.007]	[0.006]	[0.008]	[0.009]
G	Retail Trade	1.321**	1.352**	1.384**	1.383**
		[0.006]	[0.006]	[0.009]	[0.009]
H	Accommodation & Food Services	1.221**	1.316**	1.431**	1.405**
		[0.005]	[0.006]	[0.009]	[0.009]
I	Transport, Postal & Warehousing	1.452**	1.417**	1.396**	1.395**
		[0.008]	[0.008]	[0.010]	[0.010]
J	Information Media & Telecommunications	1.554**	1.263**	1.197**	1.229**
		[0.011]	[0.009]	[0.010]	[0.011]
K	Financial & Insurance Services	1.544**	1.217**	1.097**	1.140**
		[0.008]	[0.007]	[0.008]	[0.008]
L	Rental, Hiring & Real Estate Services	1.342**	1.231**	1.280**	1.315**
		[0.009]	[0.009]	[0.011]	[0.011]
M	Professional, Scientific & Technical Services	1.554**	1.261**	1.267**	1.278**
		[0.007]	[0.006]	[0.008]	[0.008]
N	Administrative & Support Services	1.252**	1.274**	1.300**	1.307**
		[0.006]	[0.007]	[0.009]	[0.009]
O	Public Administration & Safety	1.951**	1.692**	1.352**	1.383**
		[0.009]	[0.008]	[0.008]	[0.008]
P	Education & Training	1.573**	1.266**	1.166**	1.185**
		[0.007]	[0.006]	[0.006]	[0.006]
Q	Health Care & Social Assistance	3.097**	2.655**	2.471**	2.403**
		[0.016]	[0.015]	[0.016]	[0.016]
R	Arts & Recreation Services	1.358**	1.376**	1.349**	1.338**
		[0.009]	[0.010]	[0.010]	[0.010]
S	Other Services	1.200**	1.171**	1.231**	1.256**
		[0.006]	[0.007]	[0.008]	[0.008]
	Goodness-of-fit (χ^2)	98,885	276,016	274,560	340,503
	Worker characteristics	N	Y	Y	Y
	Other firm characteristics	N	N	Y	Y
	Exposure to Covid-19	N	N	N	Y

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Omitted category for industry is not in a job. See tables 5 & 10 for other variables and their associated omitted categories.

Table 7: Estimated hazard model coefficients – CWS firm types

	None (1)	Worker (2)	Firm (3)	All (4)
Low impact industry (CWS)	1.356**	1.249**	1.191**	1.224**
	[0.005]	[0.005]	[0.007]	[0.007]
Moderate impact industry (CWS)	1.261**	1.229**	1.252**	1.262**
	[0.005]	[0.005]	[0.007]	[0.007]
High impact industry (CWS)	1.188**	1.243**	1.278**	1.282**
	[0.004]	[0.005]	[0.007]	[0.007]
Public Administration & Safety	1.941**	1.687**	1.312**	1.355**
	[0.009]	[0.008]	[0.008]	[0.008]
Education & Training	1.565**	1.257**	1.123**	1.149**
	[0.007]	[0.006]	[0.006]	[0.006]
Health Care & Social Assistance	3.087**	2.637**	2.381**	2.332**
	[0.016]	[0.015]	[0.015]	[0.015]
Goodness-of-fit (χ^2)	77,300	267,900	267,219	337,436
p(low=mod)	0.000	0.000	0.000	0.000
p(low=high)	0.000	0.034	0.000	0.000
p(mod=high)	0.000	0.000	0.000	0.000
Non-recipient firm (CWS)	1.324**	1.244**	1.198**	1.233**
	[0.005]	[0.005]	[0.007]	[0.007]
Recipient firm (CWS)	1.233**	1.238**	1.261**	1.266**
	[0.004]	[0.005]	[0.007]	[0.007]
Public Administration & Safety	1.941**	1.687**	1.319**	1.361**
	[0.009]	[0.008]	[0.008]	[0.008]
Education & Training	1.565**	1.256**	1.125**	1.151**
	[0.007]	[0.006]	[0.006]	[0.006]
Health Care & Social Assistance	3.086**	2.637**	2.383**	2.333**
	[0.016]	[0.015]	[0.015]	[0.015]
Goodness-of-fit (χ^2)	74,940	267,529	267,239	337,315
p(non-recipient=recipient)	0.000	0.016	0.000	0.000
Worker characteristics	N	Y	Y	Y
Other firm characteristics	N	N	Y	Y
Exposure to Covid-19	N	N	N	Y

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Omitted category for industry is not in a job. See tables 5 & 10 for other variables and their associated omitted categories.

Table 8: Estimated hazard model coefficients – all covariates (worker characteristics)

	Industry division (1)	CWS LMH (2)	CWS Firm (3)
Female	0.975**	0.989**	0.988**
	[0.002]	[0.002]	[0.002]
Age (base month)	1.016**	1.016**	1.015**
	[0.000]	[0.000]	[0.000]
European	1.065**	1.067**	1.067**
	[0.004]	[0.004]	[0.004]
Māori	0.883**	0.882**	0.881**
	[0.003]	[0.003]	[0.003]
Pacific	0.871**	0.872**	0.872**
	[0.004]	[0.004]	[0.004]
Asian	1.293**	1.302**	1.303**
	[0.007]	[0.007]	[0.007]
MELAA	0.921**	0.923**	0.924**
	[0.010]	[0.010]	[0.010]
HQ – None	0.896**	0.893**	0.893**
	[0.004]	[0.004]	[0.004]
– Post-school	1.029**	1.023**	1.024**
	[0.002]	[0.002]	[0.002]
– Graduate	1.127**	1.129**	1.127**
	[0.003]	[0.003]	[0.003]
– Post-graduate	1.174**	1.177**	1.174**
	[0.004]	[0.004]	[0.004]
WFE	1.431**	1.419**	1.419**
	[0.005]	[0.005]	[0.005]
Flu vaccine – 2018	1.380**	1.381**	1.380**
	[0.008]	[0.008]	[0.008]
– 2019	1.394**	1.396**	1.395**
	[0.008]	[0.008]	[0.008]
– 2019 & 2018	1.591**	1.596**	1.595**
	[0.015]	[0.015]	[0.015]
– 2020	1.623**	1.625**	1.625**
	[0.005]	[0.005]	[0.005]
– 2020 & 2018	1.802**	1.806**	1.806**
	[0.015]	[0.015]	[0.015]
– 2020 & 2019	1.922**	1.928**	1.927**
	[0.012]	[0.012]	[0.012]
– All three	2.152**	2.161**	2.160**
	[0.013]	[0.013]	[0.013]
Goodness-of-fit (χ^2)	340,503	337,436	337,315

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Columns (1)-(3) match column (4) in tables 6 and 7 (upper and lower panel), respectively. See note to table 5 for omitted categories. Coefficients not reported for country of birth by recency, missing WFE, and multiple job-holder.

Table 9: Estimated hazard model coefficients – all covariates (location)

	Industry division	CWS	
		LMH	Firm
	(1)	(2)	(3)
Northland	0.803**	0.796**	0.796**
	[0.005]	[0.005]	[0.005]
Waikato	0.938**	0.929**	0.928**
	[0.003]	[0.003]	[0.003]
Bay of Plenty	0.794**	0.788**	0.788**
	[0.003]	[0.003]	[0.003]
Gisborne	0.983	0.964**	0.963**
	[0.010]	[0.010]	[0.010]
Hawke's Bay	0.949**	0.935**	0.934**
	[0.005]	[0.005]	[0.005]
Taranaki	0.800**	0.789**	0.788**
	[0.005]	[0.004]	[0.004]
Manawatū-Whanganui	0.952**	0.943**	0.942**
	[0.005]	[0.004]	[0.004]
Wellington	0.938**	0.939**	0.939**
	[0.003]	[0.003]	[0.003]
West Coast	0.858**	0.844**	0.843**
	[0.011]	[0.010]	[0.010]
Canterbury	0.839**	0.834**	0.834**
	[0.002]	[0.002]	[0.002]
Otago	1.137**	1.127**	1.126**
	[0.005]	[0.005]	[0.005]
Southland	0.896**	0.884**	0.881**
	[0.006]	[0.006]	[0.006]
Tasman	0.864**	0.851**	0.851**
	[0.009]	[0.009]	[0.009]
Nelson	0.977*	0.971**	0.971**
	[0.010]	[0.010]	[0.010]
Marlborough	1.049**	1.036**	1.033**
	[0.011]	[0.011]	[0.011]
Goodness-of-fit (χ^2)	340,503	337,436	337,315

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Columns (1)-(3) match column (4) in tables 6 and 7 (upper and lower panel), respectively. Omitted category is Auckland Regional Council.

Table 10: Estimated hazard model coefficients – all covariates (firm & exposure)

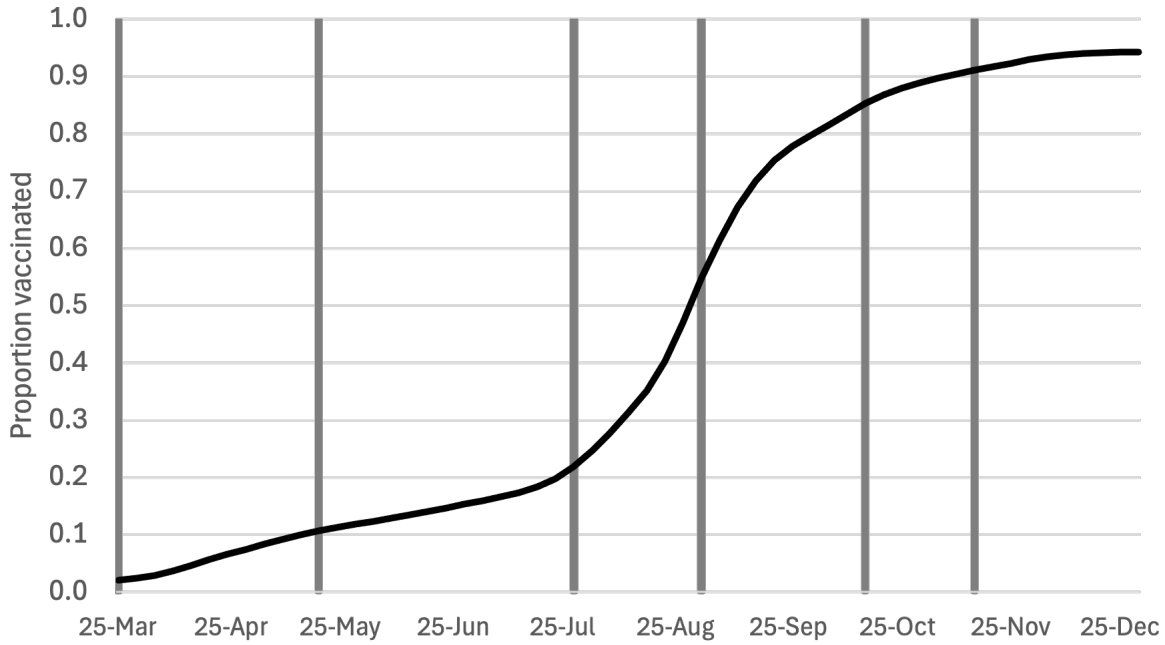
	Industry	CWS	
	division	LMH	Firm
	(1)	(2)	(3)
Private-for-profit firm	0.881**	0.879**	0.882**
	[0.003]	[0.003]	[0.003]
FFE	1.284**	1.148**	1.130**
	[0.010]	[0.008]	[0.008]
Firm size, ln(firm FTE)	0.990**	0.994**	0.994**
	[0.001]	[0.001]	[0.001]
Firm has WP(s)	1.007**	0.999	0.996
	[0.002]	[0.002]	[0.002]
Worker has had Covid-19	1.108*	1.112*	1.112*
	[0.052]	[0.052]	[0.052]
Worker has had Covid-19 recently	0.896	0.892*	0.893*
	[0.054]	[0.053]	[0.054]
Worker has had vaccinated co-worker	1.753**	1.763**	1.764**
	[0.004]	[0.004]	[0.004]
Worker has had Covid-19 co-worker	1.115**	1.116**	1.116**
	[0.004]	[0.004]	[0.004]
Goodness-of-fit (χ^2)	340,503	337,436	337,315

**;* coefficient significantly different from one at 1%;5% level (robust standard errors in brackets). Columns (1)-(3) match column (4) in tables 6 and 7 (upper and lower panel), respectively. Omitted category is not-for-profit firm; employee-only firm; and worker hasn't had each Covid-19 "exposure." Coefficient not reported for missing FFE.

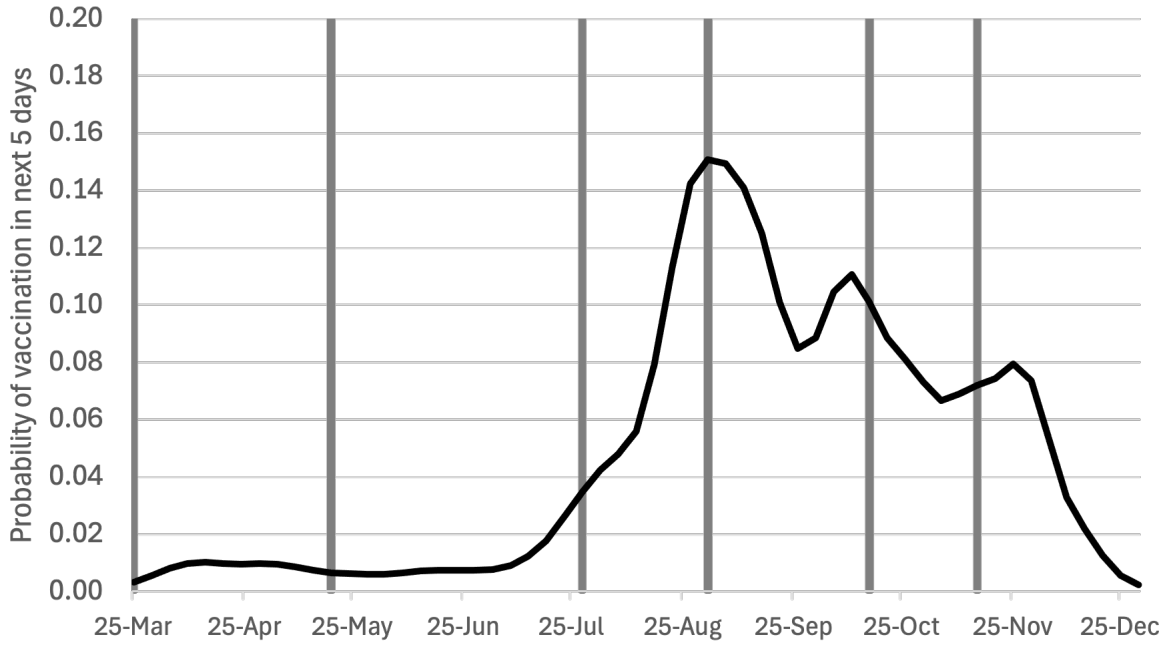
Figures

Figure 1: Vaccination rate for worker population

(A) Vaccination rate

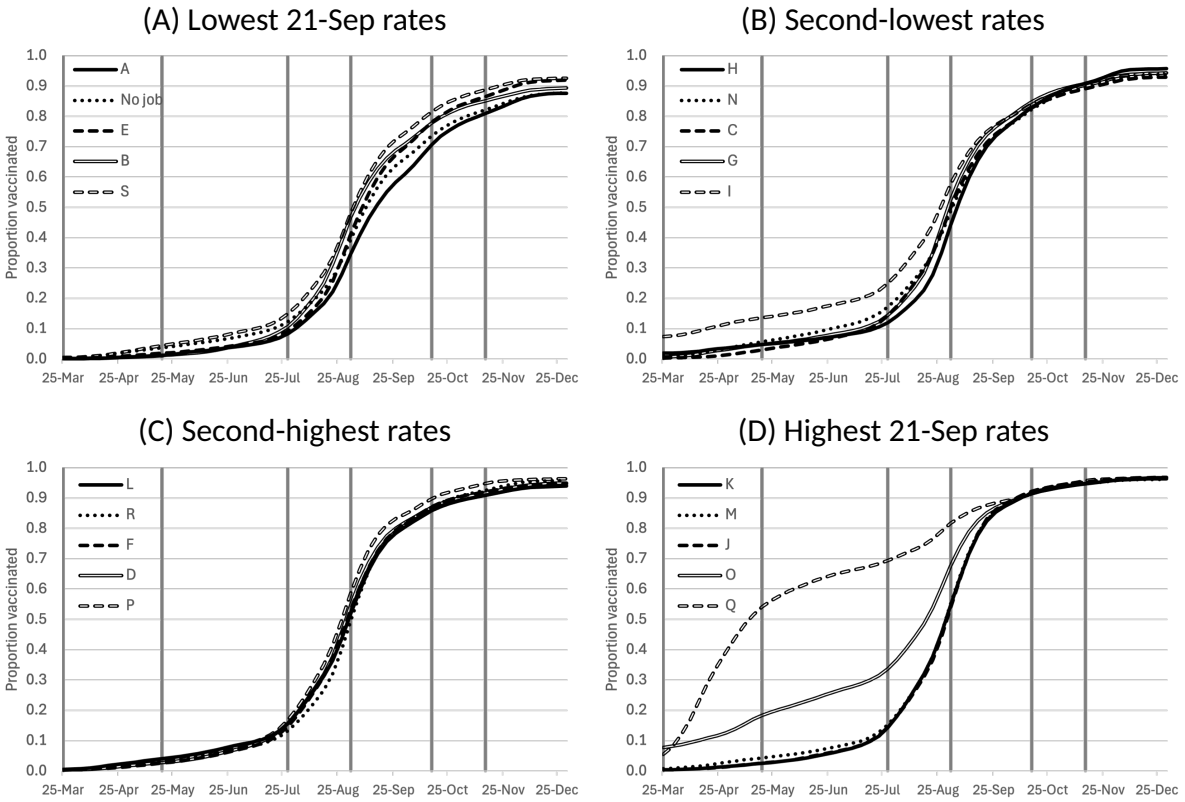


(B) Hazard rate



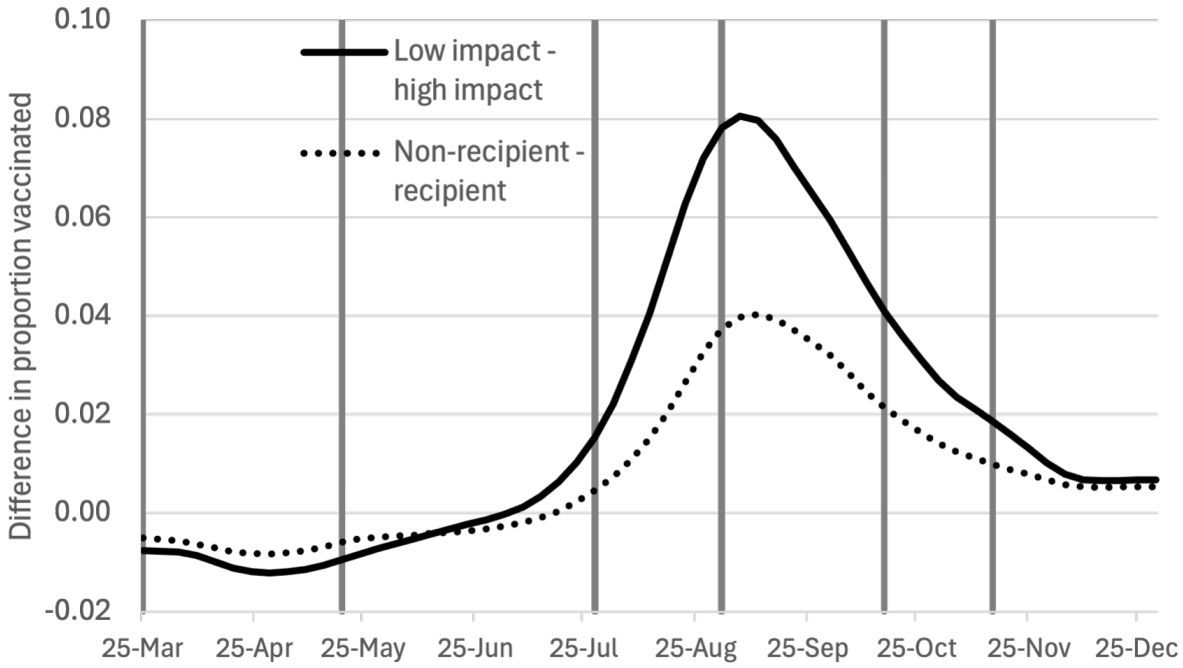
The vaccination rate is smoothed (using Stata procedure lpoly with default options) to satisfy confidentiality requirements. The hazard rate is derived from the smoothed vaccination rate and is the probability of being vaccinated in the following five days (the interval between points in panel A). Vertical lines highlight key dates in the vaccine roll-out: 25-Mar (health); 17-May (65+); 28-Jul (pop by age); 1-Sep (all); 16-Oct (Super Saturday); 17-Nov (vaccine pass).

Figure 2: Vaccination rate by industry division



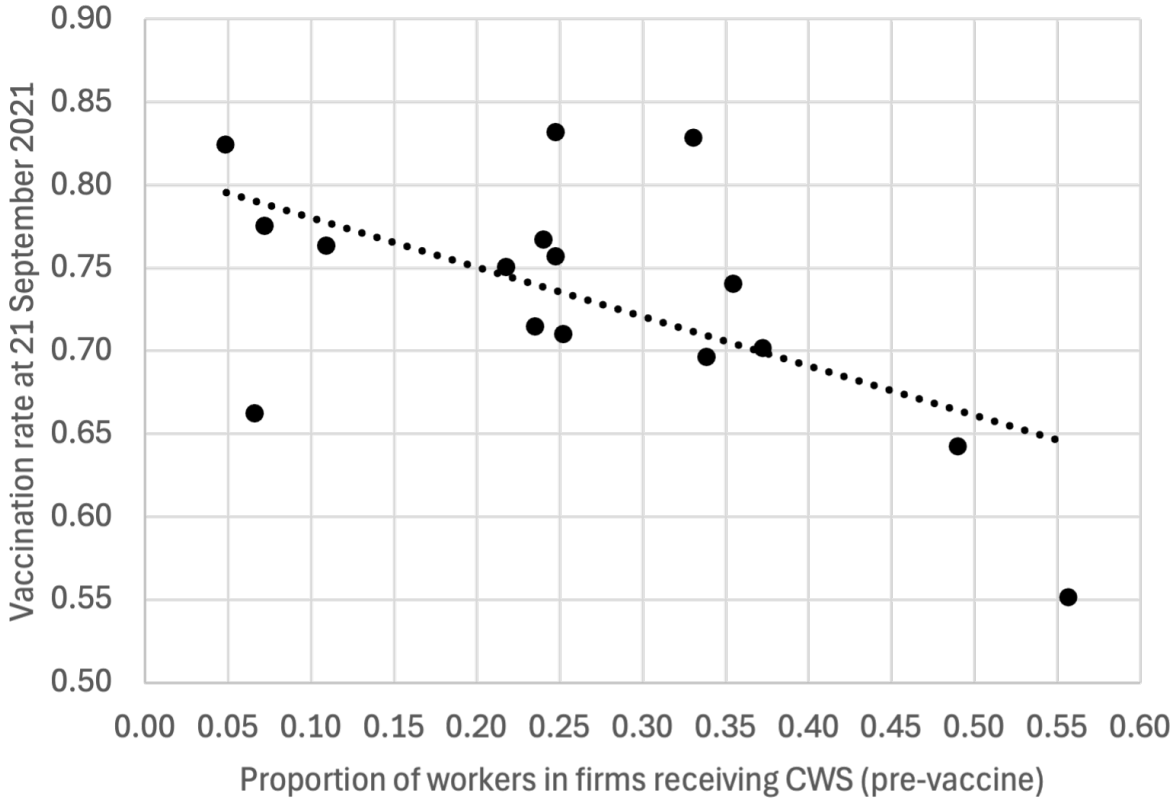
See figure 1 for notes. Industries ranked by vaccination rate on 21-Sep, from lowest to highest.

Figure 3: Difference in vaccination rates by firm CWS type



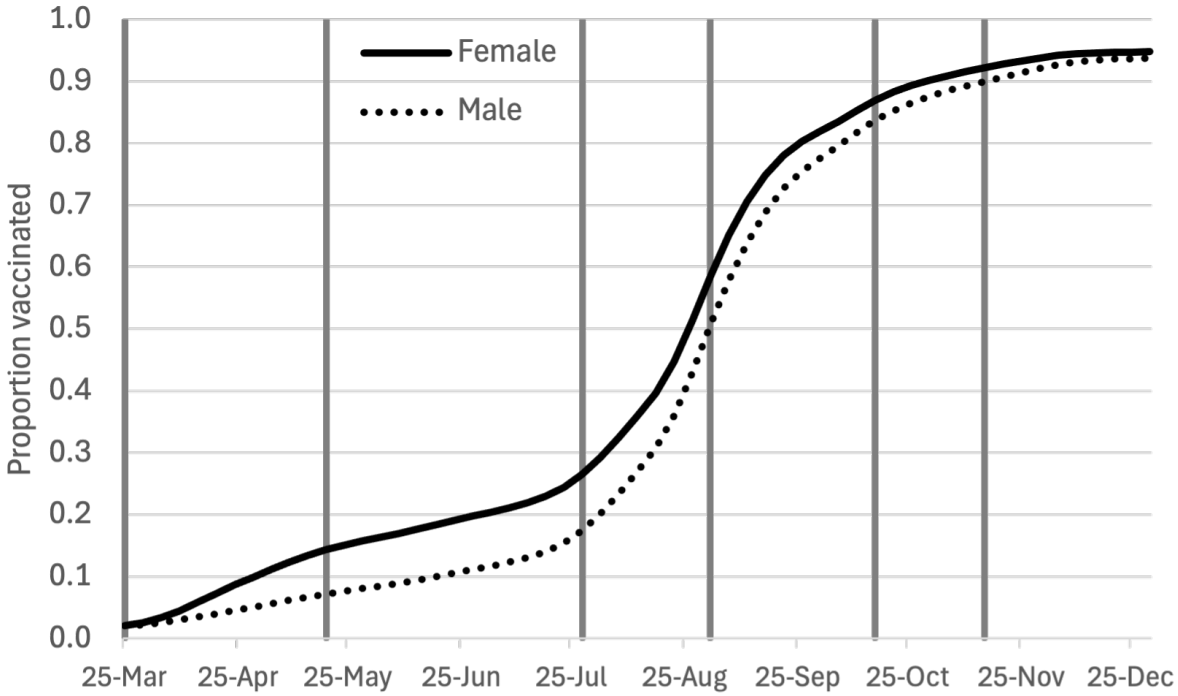
Plot is difference in smoothed vaccination rate (see figure 1 notes) between: firms in low & high impact industries; and Covid Wage Subsidy non-recipients & recipients. Public sector dominated industries (O, P, Q) and not in a job excluded.

Figure 4: Correlation between CWS uptake & 21 September 2021 vaccination rate by industry



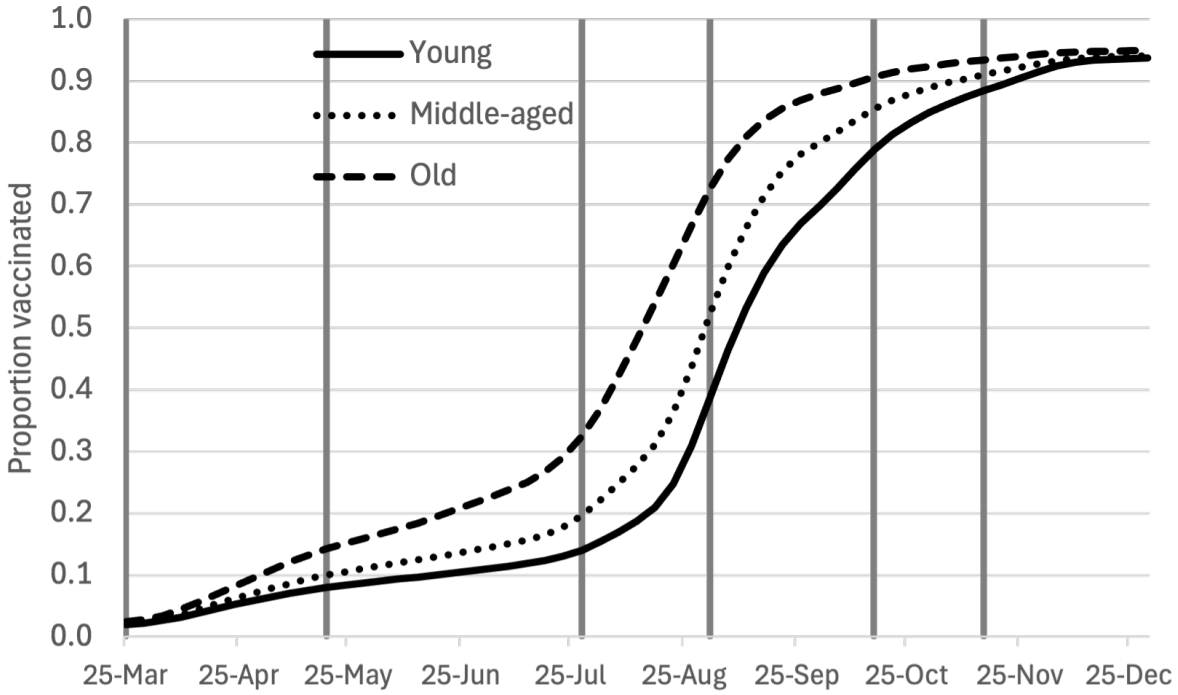
Vaccination rates at 21 September 2021 reported in table 2. Pre-vaccine CWS uptake rate reported in table 4. Public sector dominated industries (O, P, Q) and not in a job excluded. Dotted line is unweighted linear fit with slope -0.297 and constant 0.810 (R^2 = 0.344). Correlation is -0.586.

Figure 5: Vaccination rate by sex



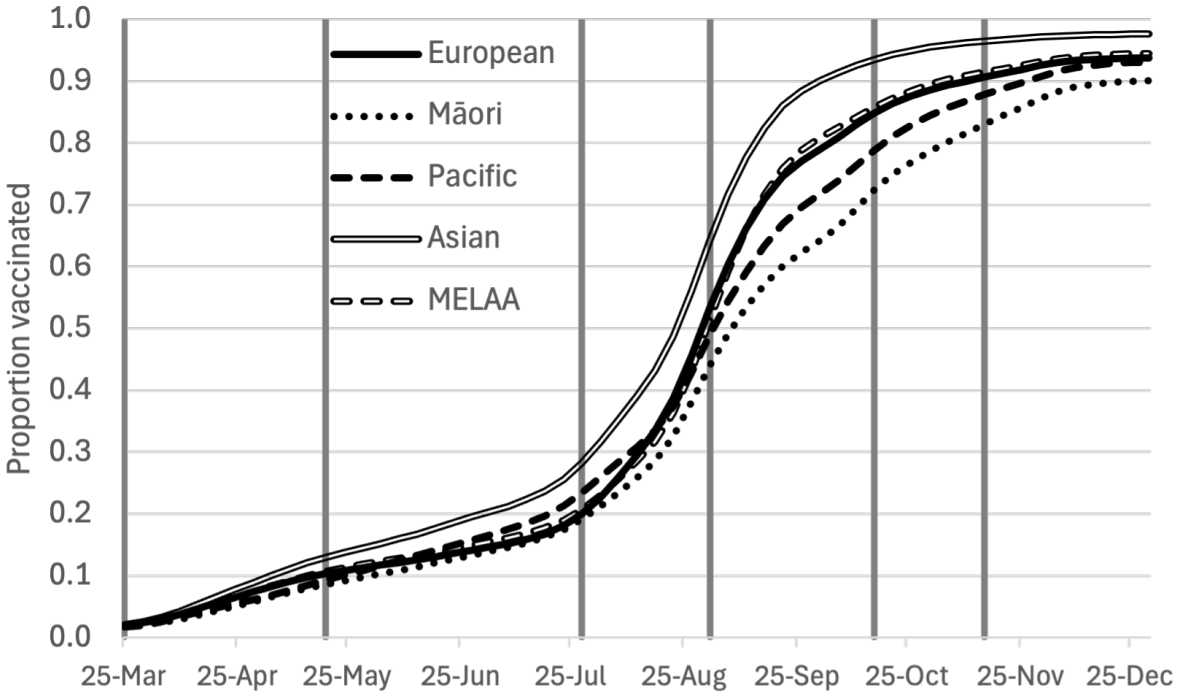
See figure 1 for notes.

Figure 6: Vaccination rate by age groups



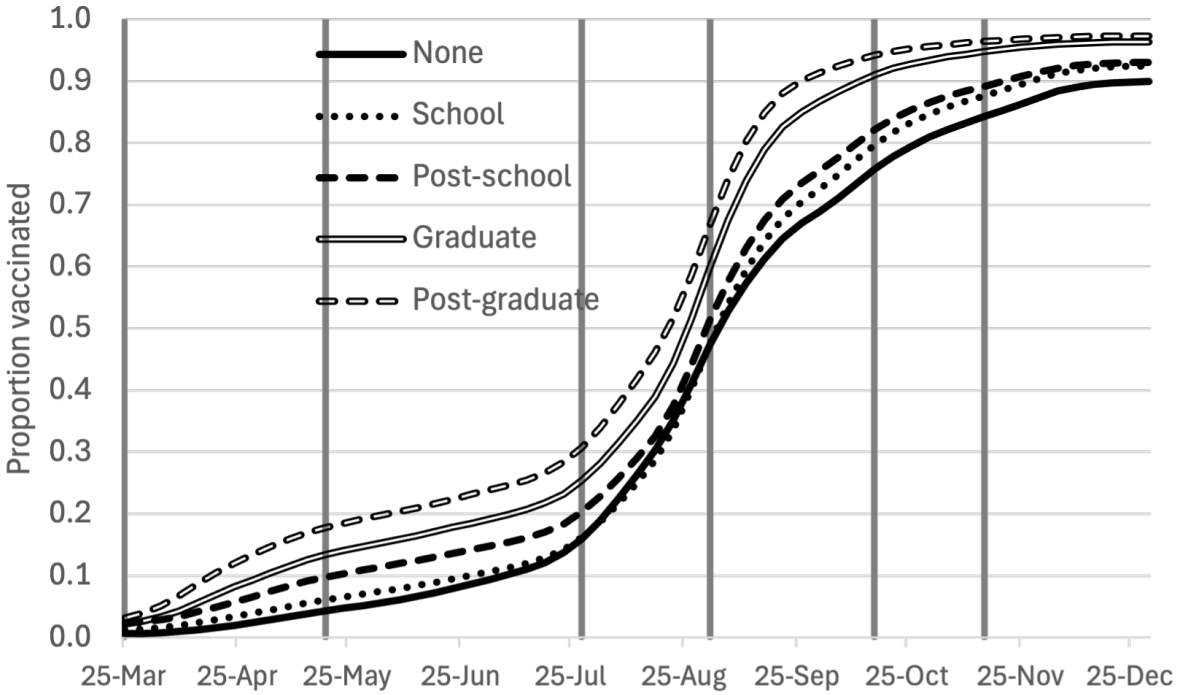
See figure 1 for notes. Age groups are: young (18-29); middle-aged (30-50); old (51-64).

Figure 7: Vaccination rate by ethnicity



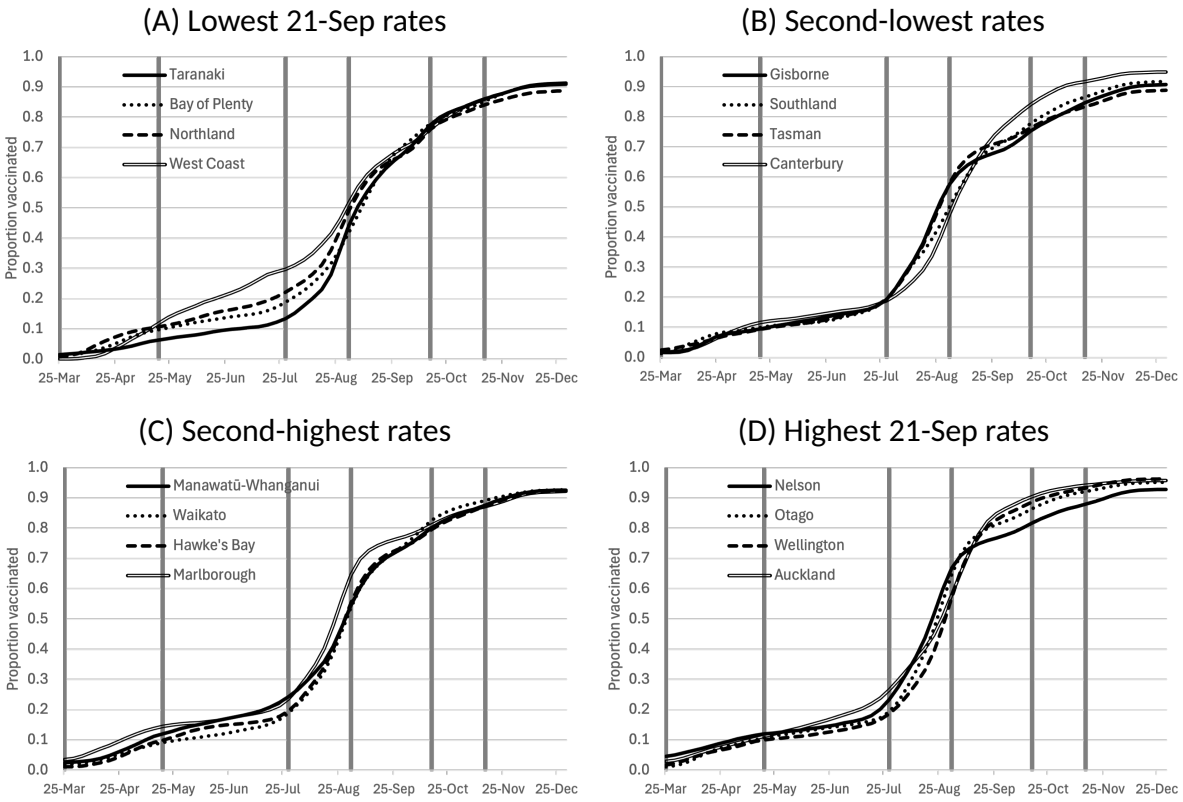
See figure 1 for notes. Ethnicity is multiple response ("Other" ethnicity grouped with European).

Figure 8: Vaccination rate by highest qualification



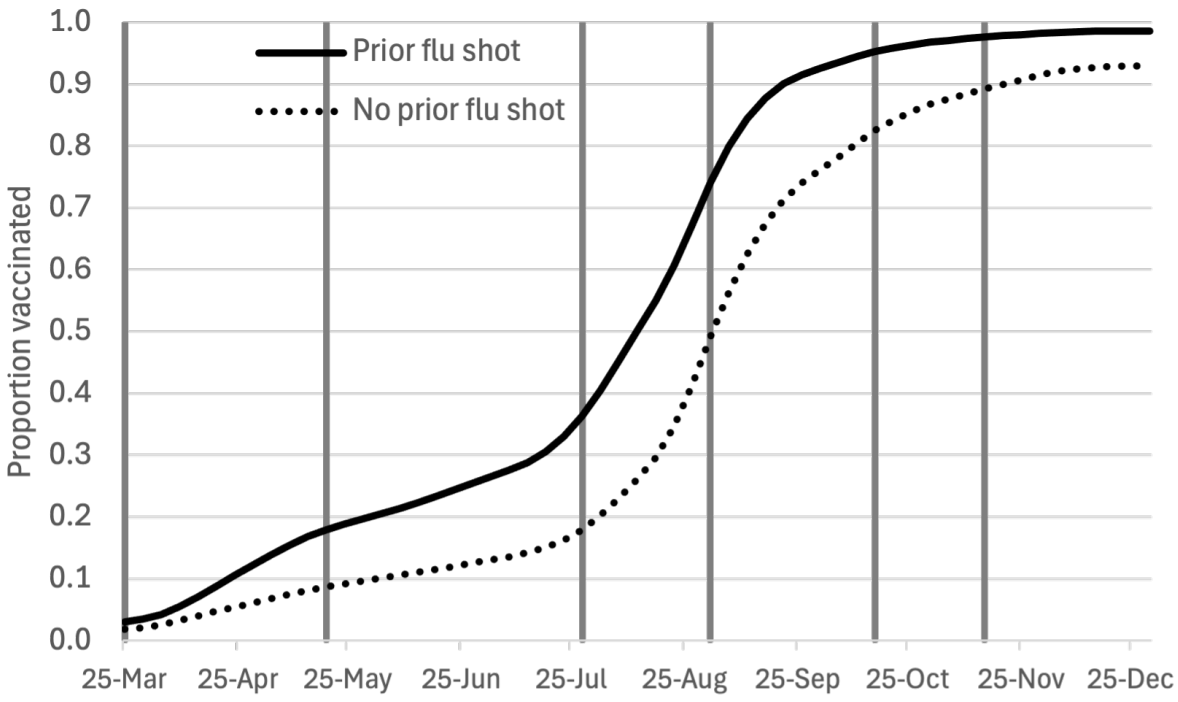
See figure 1 for notes.

Figure 9: Vaccination rate by Regional Council



See figure 1 for notes. RCs ranked by vaccination rate on 21-Sep, from lowest to highest.

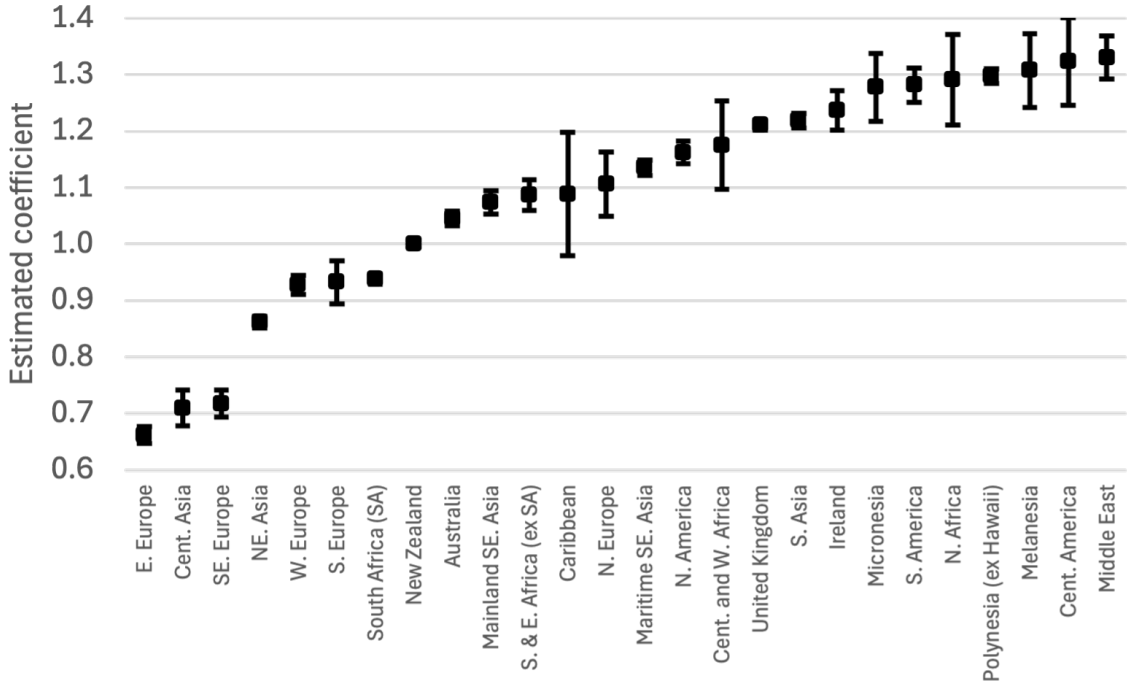
Figure 10: Vaccination rate by prior influenza vaccination



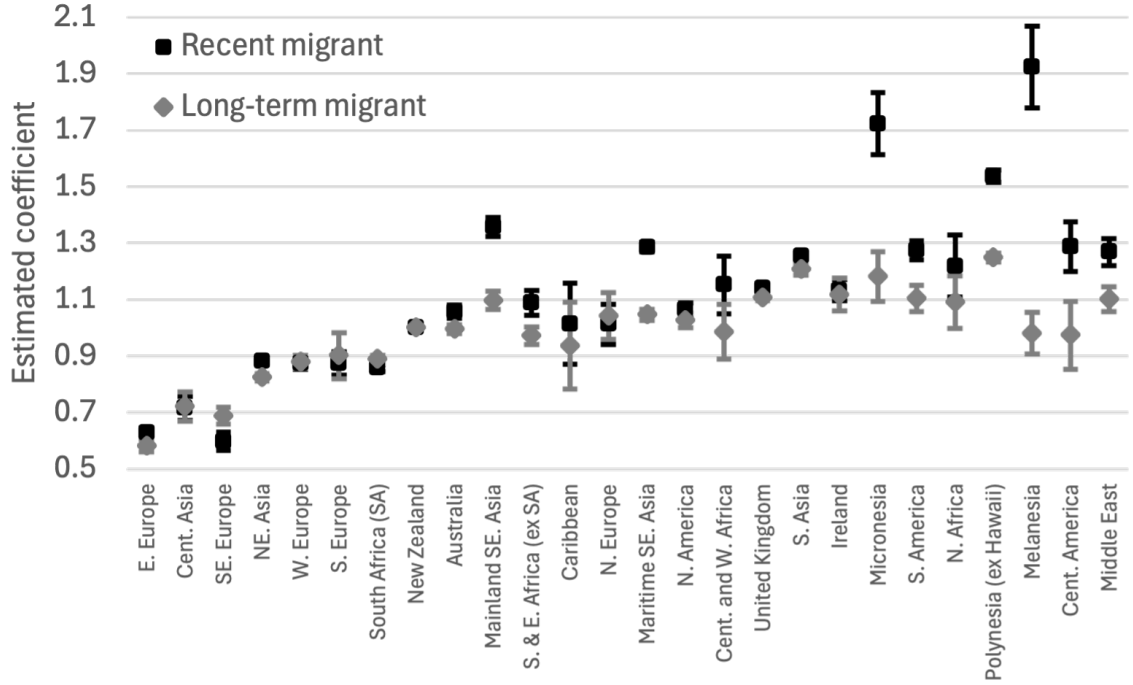
See figure 1 for notes. Prior flu vaccination is any of the three prior calendar years (2018-2020).

Figure 11: Estimated hazard model coefficients for country of birth

(A) Controls for sex, age & ethnicity

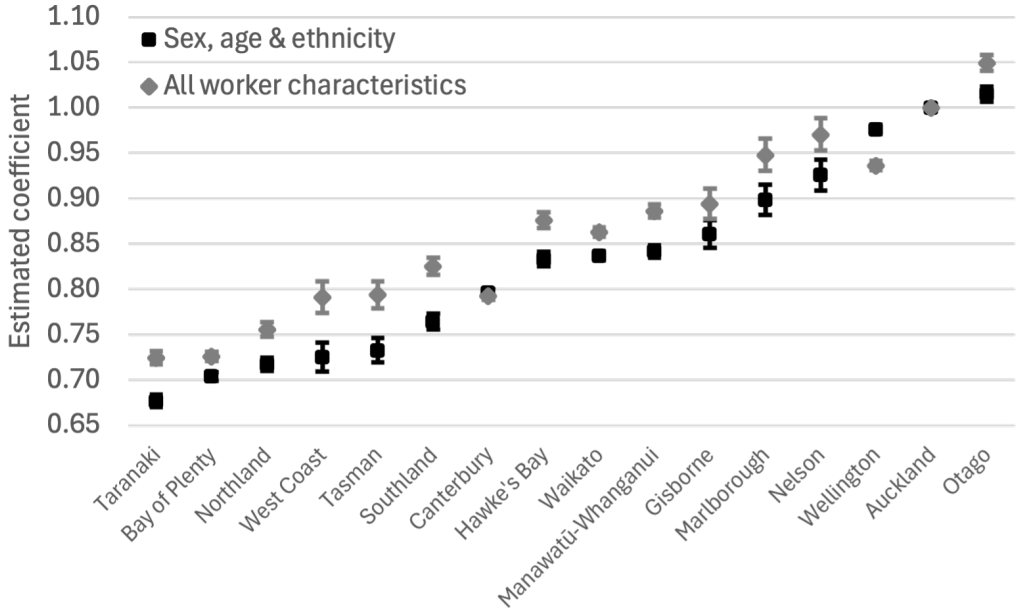


(B) All worker characteristics included & by recency of arrival



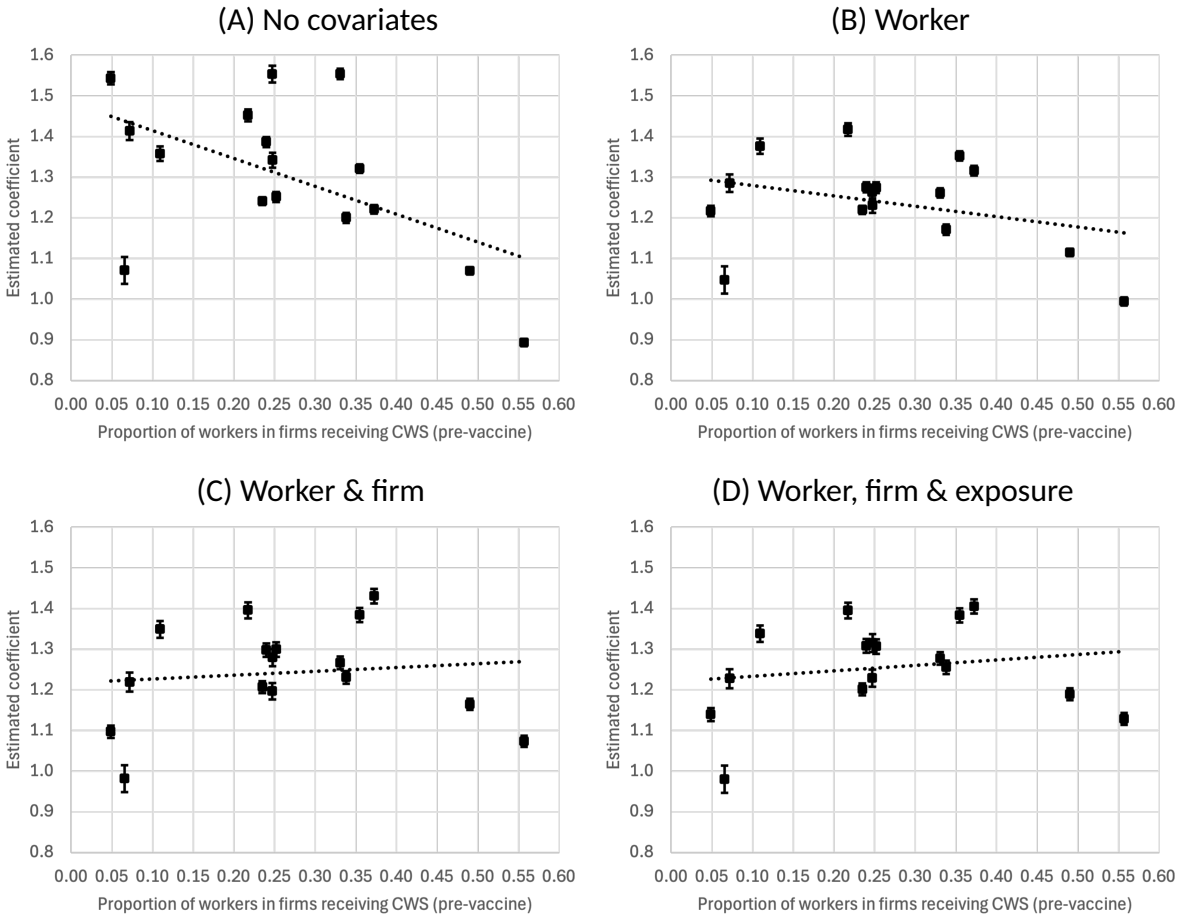
Estimated coefficients from table 5 models – columns (3) and (8) for panels (A) and (B) respectively. Country of birth is ordered by estimates in panel (A). Stats NZ two-digit geographic region used, except for the country South Africa, which is separated from its region (South and East Africa). 95% confidence interval included (robust standard errors). Omitted category is New Zealand (included for reference).

Figure 12: Estimated hazard model coefficients for Regional Council



Estimated coefficients from table 5 models – "sex, age & ethnicity" (column 6) and "all worker characteristics" (column 8). 95% confidence interval included (robust standard errors). Omitted category is Auckland Regional Council (included for reference).

Figure 13: Correlation between CWS uptake and hazard model coefficients for industry



Estimated coefficients from table 6 models. 95% confidence interval included (robust standard errors). Omitted category (not in a job) and public sector dominated industries (O, P, Q) excluded. Dotted line is unweighted linear fit. Correlation is -0.530 (A); -0.328 (B); 0.112 (C); 0.172 (D).

A. Appendix – Metadata for new Fabling-Maré IDI_Adhoc table

Table A.1: IDI_Adhoc.clean_read_IR.characteristics_Lpop_IDI_YYYYMM_RFabling

Variable	Format	NULL	Description
snz_uid [KEY]	int	N	Individual identifier
ever_employee	tinyint	N	Indicator for ever an employee
ever_WP	tinyint	N	Indicator for ever a working proprietor
fem	tinyint	Y	Indicator for female
wfe	float	Y	Estimated two-way worker wage fixed effect
highest_qual_source	char(3)	N	Data source for highest qualification (hq)
hq_none	tinyint	N	Indicator for hq=none
hq_schl	tinyint	N	Indicator for hq=school
hq_pschl	tinyint	N	Indicator for hq=post-school
hq_grad	tinyint	N	Indicator for hq=graduate
hq_pgrad	tinyint	N	Indicator for hq=post-graduate
descent_maori_source	varchar(4)	Y	Data source for Māori descent
des_maori	tinyint	Y	Indicator for Māori descent
birth_nz_source	char(3)	N	Data source for NZ-born
birth_nz	tinyint	N	Indicator for NZ-born
country_of_birth_source	char(3)	Y	Data source for country of birth (cob)
cob_2d	tinyint	Y	Country of birth (level two)
cob_uk	tinyint	Y	Indicator for cob=United Kingdom
cob_ireland	tinyint	Y	Indicator for cob=Ireland
cob_nth_america	tinyint	Y	Indicator for cob=North America
cob_sth_africa	tinyint	Y	Indicator for cob=South Africa
arrival_live_nz_source	varchar(15)	Y	Data source for month of arrival to live in NZ
arr_live_nz_mth	int	Y	Month of arrival to live in NZ (YYYYMM)

Data source codes (alphabetically): Administrative Population Census (APC); Census (CEN); Department of Internal Affairs (DIA); Department of Labour (DOL); Household Labour Force Survey (HLFS); and imputed (IMP). Currently, the data source code for arrival month is more verbose, but will be streamlined in subsequent instances to match other source variable coding. Sex (female indicator) comes from the IDI personal details table. Other variables, including imputation methods, are described in: employee/WP (Fabling and Maré 2015); worker fixed effect (Maré and Fabling 2025); highest qualification (Maré et al. 2023); Māori descent (Fabling and Maré 2024); and country of birth & month of arrival to live (Fabling et al. 2022).