INTERNATIONAL MONETARY FUND

What Matters for Job Finding and Separation in the Long Run?

Evidence from Labor Market Dynamics in New Zealand

Guanyu Zheng, Gulnara Nolan, Christopher Ball, Siddharth Kothari and Yosuke Kido

WP/22/172

2022
SEP

WORKING PAPER

 WP/22/172

IMF Working Paper
Asia and Pacific Department

What Matters for Job Finding and Separation in the Long Run? Evidence from Labor Market Dynamics in New Zealand

Prepared by Guanyu Zheng, Gulnara Nolan, Christopher Ball, Siddharth Kothari and Yosuke Kido*

Authorized for distribution by Harald Finger
October 2022

ABSTRACT: We use the novel anonymized Household Labour Force Survey (HLFS) microdata to analyze job finding rates and job separation rates in New Zealand. We find that individual characteristics, including age, gender, ethnicity and education have a significant impact on job finding and separation rates, even after controlling for other factors. We use a decomposition approach to analyze how the effects of individual characteristics on job finding and separation rates contribute to heterogeneity in employment outcomes. Overall, we find that higher separation rates of young workers play a disproportionate role in explaining heterogeneity of employment outcomes across age groups, while differences in finding rates are somewhat more important in explaining differences by education level. Both finding and separation rate differences are important in explaining differences across ethnicities. We also find some heterogeneous response of worker groups to business cycle after controlling for other factors. The results underscore the importance of well-targeted labor market support policies.

JEL Classification Numbers:	E24, J62, J63
Keywords:	Labor market dynamics; Gross worker flows; Unemployment variability

Author's E-Mail Address:	guanyu.zheng@mbie.govt.nz; nolang@rba.gov.au; christopher.ball@rbnz.govt.nz; SKothari@imf.org; YKido@imf.org

* Zheng: Ministry of Business, Innovation and Employment; Nolan: Reserve Bank of Australia; Ball: Reserve Bank of New Zealand; Kido and Kothari: IMF.

WORKING PAPERS

What Matters for Job Findings and Separation in the Long Run?

Evidence from Labor Market Dynamics in New Zealand

Prepared by Guanyu Zheng, Gulnara Nolan, Christopher Ball, Siddharth Kothari and Yosuke Kido[1]

[1] We are grateful to Harald Finger and Ippei Shibata for their helpful comments. We thank Statistics New Zealand for their help with labor market data. The views expressed herein are those of the authors and do not necessarily represent the views of the Reserve Bank of Australia, Reserve Bank of New Zealand, Ministry of Business, Innovation and Employment, the International Monetary Fund, the IMF's Executive Board, or IMF management.

Contents

1. Introduction 5

2. Labor Market Indicators in New Zealand 6

2.A. Dispersion across groups 6

2.B. The Household Labour Force Survey micro-level data 6

3. Labor Market Dispersion: Heterogeneity Across Worker Groups 7

3.A. Methodology: Micro-level Regressions 8

3.B. Results of Micro-level Regressions 9

3.C. Methodology: Counterfactual Analysis for Steady State Unemployment Rates 11

3.D. Results of Counterfactual Analysis 12

4. Heterogenous Response to Business Cycles 14

5. Conclusion 15

Appendix 1. Robustness Checks 25

References 27

TABLES

Table 1. Labor Market Indicators of Worker Groups 18

Table 2. Job-finding regressions: Probit Regression 19

Table 3. Job-exit Regressions: Probit Regression 20

Table 4. Decomposition of Steady State Non-employment Rates 21

Table 5. Decomposition of Steady State Unemployment Rates 22

Table 6. Job-finding Regressions with Business Cycle Interaction Terms 23

Table 7. Job-exit Regressions with Business Cycle Interaction Terms 24

1. Introduction

Aggregate labor market outcomes depend on complex dynamics, including the flows into and out of unemployment as well as job-to-job transitions (Clark and others, 1979). More flexible labor markets tend to have greater turnover, characterized by higher job-finding rates (probability of an individual moving from being unemployed to employed) and job-separation rates (probability of an individual moving from being employed to unemployed).

The heterogeneity in labor market dynamics is an increasingly important topic in labor and macroeconomics and policy formulation (e.g. Ahn and Hamilton 2020). For example, in the US, race and gender differential in the labor market remain stubbornly persistent (e.g. Altonji and Blank, 1999). The question is whether the high unemployment rates among certain ethnicity and age groups are driven by high separation rates or low job finding rates. For the United States, even at the aggregate level, views have diverged (e.g., Hall, 2005; Shimer, 2012; Yashiv, 2007; Fujita and Ramey, 2009).

In this paper, we utilize novel anonymized New Zealand Household Labour Force Survey (HLFS) microdata to study what workers' characteristics affect differences in labor market outcomes. New Zealand is an interesting example to study as gross labor market flows are relatively large and there is significant heterogeneity in labor market conditions across worker groups (e.g. Elsby and others, 2013; Ball and others, 2020; Sin and others, 2020). Utilizing micro-level labor market flow data, we first investigate how individual characteristics affect job finding and separation rates, simultaneously controlling for age, gender, ethnicity and qualification, and other individual characteristics (e.g. industry, occupation, region and unemployment spell). In addition, we employ a decomposition method based on a simple steady state relation between the unemployment rate, and finding and separation rates (see for example, Shimer, 2005, 2012) to quantify how differences in job finding and separation rates across groups translate into differences in unemployment rates.[2] We also explore cyclical heterogeneity across groups by extending our benchmark regression model.

We find a significant role for individual characteristics in determining job finding and separation rates. On job finding rates, we find that older workers, non-European ethnic groups (Māori and Pacific people), and less educated workers tend to have lower job finding rates after controlling for the business cycle and other factors, with the length of unemployment spells also affecting job finding probabilities. On job separation rates, young workers, Māori and Pacific people, and less-educated individuals tend to have higher separation rates. The differences in separation and finding rates for women compared to men depend on the sample used. Labor market dynamics for women are worse when looking at a broad sample that includes people not in the labor force but not so when focusing on a narrow sample of employed and unemployed people only, indicating that women are less likely than men to move from outside of the labor force to employment and more likely to leave the labor force from employment. We also find some cyclical heterogeneity across worker groups. With regard to age, youth workers tend to have more cyclical job finding rates, while older workers tend to have more cyclical separation rates. Māori and Pacific people also tend to have more cyclical job finding rates, while workers who have only completed high school tend to have more cyclical job exit rates compared to those with higher degrees.

[2] By non-employment rate we mean the share of working age population that is either unemployed or not participating in the labor force.

Accounting of unemployment rates also sheds light on the contribution of labor market flows to differences in levels of unemployment rates. On age, we find that the higher unemployment or non-employment rates for youth workers and workers aged 25-39 can be attributed to higher separation rates rather than lower finding rates. This finding is consistent with observation by Choi and others (2015), which investigate US Current Population Survey and find high youth unemployment rate is due to high employment exit probabilities. By contrast, for relatively older workers aged 54-65, the higher unemployment and non-employment rate compared to other prime aged workers can be mainly attributed to lower job finding rates. This finding is different from the prediction by Hairault and others (2015), which argue that older workers leave jobs because the value of employment decays as they get closer to retirement. Our findings also shed light on dispersion among worker groups with different ethnicities and educational background. On ethnicity, both the differences in separation and finding rates play a role in explaining dispersion of the unemployment/non-employment rates, while finding rates play a more important role for differences across education levels.

Our study is related to a growing literature discussing dispersion in labor market outcomes. While previous research often focuses on some dimension of individual characteristics without controlling for other characteristics, this paper controls for possible impacts from individual characteristics simultaneously using rich, granular data, and analyzes the marginal effects of each characteristic on gross labor market flows. We also use a decomposition approach to quantify the relative importance of job finding and exit rates in explaining the variation in unemployment rates of different worker groups.

The rest of the paper is structured as follows. Section II describes heterogeneity across workers in New Zealand's labor market and provides an overview of the main dataset we use in the paper, the anonymized confidential New Zealand HLFS micro-level data. Section III analyzes drivers of heterogeneity in job finding and separation rates, and assesses how they contribute to differences in unemployment rates among worker groups. Section IV explores cyclical behavior of job finding and separation rates, while Section V concludes.

2. Labor Market Indicators in New Zealand

A. Dispersion Across Groups

New Zealand is a suitable example to study heterogeneity in employment outcomes. For example, Sin and others, (2020) explore the gender gap in wages in New Zealand's labor market using the Linked Employee Employer Data and find wage gaps within firms. Hyslop and others, (2019) analyze dispersion in labor force participation rates among age groups, gender, and ethnicity, using labor market data from 1986 to 2017.

Over the sample period 2006-2021, the aggregate unemployment rate has averaged around 5 percent, with peaks after the global financial crisis and during COVID (Figure 1). Aggregate finding and separation rates have also fluctuated with the business cycle (Figure 2).

Furthermore, given our focus on heterogeneity in labor market outcomes across groups, we find that some worker groups, such as female, youth, and workers with non-European ethnicities have persistently higher unemployment rates than the aggregate (Table 1). The question is whether the high unemployment rates or non-employment rates among certain ethnicity and age groups are driven primarily by high separation rates or low job finding rates. In the following sections, we analyze labor market flows for New Zealand for different worker groups and analyze heterogeneity.

B. The Household Labour Force Survey Micro-level Data

The micro-level New Zealand Household Labour Force Survey (HLFS) is our primary data source. The HLFS is a quarterly survey which collects employment status and personal-level information from 15,000 households (approximately 30,000 individuals over age 15) living in private dwellings in New Zealand. It is the main data source to produce the official estimates of quarterly employment and unemployment rates for New Zealand. It contains a rich set of information on individual characteristics, as well as other relevant information such as sectors, regions, and unemployment spells, making it suitable for analysis of the determinants of employability at a granular level.

The HLFS has a rotating panel survey design which repeatedly surveys respondents living in the same dwellings over a set of consecutive quarters.[3] By its sampling design, one-eighth of the rotation panel is rotated out of the survey and replaced by a new panel of dwellings. In other words, there is always an overlap of seven-eighths of the panels from one quarter to another – roughly 13,000 households and 26,000 individuals. This longitudinal feature of the HLFS allows us to analyze job finding and job separation at the individual level from one quarter to the next.

However, the actual number of individuals who remain in the sample over two consecutive quarters is smaller, due to individuals moving from their home addresses or not responding to the survey (over 2013—2016, the response rate was around 85 percent). Young (less than 30 years of age), non-European, and sole-person households show a greater likelihood of missing the survey, suggesting a need to control for potential selection bias. We scale up sampling weights of the sub-populations associated with age, ethnicity and household type characteristics to compensate for the higher drop-out rates.

The scaling-up approach takes several iterations. First, we calculate quarterly population estimates by age-ethnicity-household type using HLFS sampling weights and take averages over two consecutive quarters. Then, we repeat the same calculations for those remaining in the survey over two adjacent quarters. Lastly, the ratio between the above population estimates is the scaling factor which is used to adjust the sampling weights.

3. Labor Market Dispersion: Heterogeneity Across Worker Groups

We exploit the panel dimension of the HLFS microdata to explore how labor market dynamics (job finding and separation rates) differ across groups and how these contribute to differences in aggregate unemployment rate and labor force participation.[4]

[3] A surveyed individual or household can stay in the survey for up to eight consecutive quarters.

[4] 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 Statistics Act 1975. The results presented in this study are the work of the authors, not Stats NZ or individual data suppliers. 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/.

A. Methodology: Micro-level Regressions

We exploit the panel dimension of the HLFS to construct dummy variables for when an individual transitions from employment to unemployment (job-exit rates) and from unemployment to employment (job-finding rate). To analyze the **job-finding rate**, we define a dummy variable $f_{i,t}$ which takes value 1 if an individual was unemployed in quarter t but became employed in quarter t+1, and 0 if an individual was unemployed in quarter t and was not employed in quarter t+1.

$$f_{i,t} = \begin{cases} 1 & \textit{individual } i \textit{ is unemployed in } t \textit{ but employed in } t+1 \\ 0 & \textit{individual } i \textit{ is unemployed in } t \textit{ and not employed in } t+1 \end{cases}$$

To analyze the **job-exit rate**, we define a dummy variable $s_{i,t}$ which takes value 1 if an individual was employed in quarter t but became unemployed in quarter t+1, and 0 if an individual was employed in quarter t and was not unemployed in quarter t+1

$$s_{i,t} = \begin{cases} 1 & \textit{individual } i \textit{ is employed in } t \textit{ but unemployed in } t+1 \\ 0 & \textit{individual } i \textit{ is employed in } t \textit{ and not unemployed in } t+1 \end{cases}$$

Narrow vs broad measure of "unemployment": In the baseline, we use a broad sample which includes all individuals aged 15-64 not in the labor force (NILF), and in effect count them as not employed when defining the above dummy variables. Therefore, in effect we are measuring the non-employment rate and entry and exit from employment (both into and out of unemployment and NILF). While this is not the usual definition for unemployment and job-finding and exit rates used in the literature, we use it as the baseline as it maximizes the sample size in our regressions and gives a broad sense of the combined unemployment and participation dynamics of different groups aged between 15 to 64. As a robustness check, we also consider a narrower sample where we exclude all individuals not in the labor force, which is consistent with the standard definition of unemployment.

Regression: To study the determinants of job-finding rates and job-exiting rates, we run panel probit regressions of the following form:

$$\Pr\left(Y_{i,t} = 1 | X_{i,t}, Z_{i,t}, G_t\right) = \Phi(\alpha + \beta X_{i,t} + \gamma Z_{i,t} + \sigma G_t + \epsilon_{i,t}) \quad (1)$$

where $Y_{i,t}$ can be the job-finding or job-exit dummies defined above, X_i are categorical variables for different groups of interest, $Z_{i,t}$ includes rich set of observable controls discussed below, and G_t is a control for the aggregate business cycle, proxied by annual (four-quarter average) GDP growth per capita. For a robustness check, we also run regressions with the output gap estimated by Reserve Bank of New Zealand (Jacob and Robinson, 2019), instead of GDP per capita. As the left-hand side variable is a binary dummy, we estimate probit regressions. The estimates of β directly capture the extent to which finding and exit rates differ across categories in a group after controlling for other factors.

The individual-level characteristics included in the regressions vary depending on the transition probability being considered. Four key characteristics for studying heterogeneity are included in all regressions. These are: (i) highest qualification level categorized into four groups—less than high-school, high-school, post-school but less than bachelors, and bachelors or more; (ii) ethnicity categorized into four groups—European, Māori, Pacific People, and Others;[5] (iii) age categorized into four groups—15 to 24, 25 to 39; 40 to 54; 55 to 64, and (iv) gender—male and female. In addition, household type (individual, couple, couple with children, single parent), regional council dummies, and quarter-fixed effects (to pick up seasonality in finding and exit rates) are included in both regressions as controls.

In addition to the above variables, we also include two additional variables in the finding rate regressions. The first is a measure of unemployment duration, which can take three values: unemployed less than a year, unemployed more than a year, and never employed. To the extent that longer-term unemployed have lower finding rates, including this variable can test for scarring effects of unemployment. For the "broad" sample, we also include a dummy for an individual not being in the labor force, to control for the fact that retired individuals or students may have low finding rates.

For the finding-rate regressions, control variables $Z_{i,t}$ include dummy variables for family type and regional information. Previous studies find that family type can be relevant for labor market outcomes (e.g. Alesina, and others, 2015; Baker and Benjamin, 1997). Regional information also controls for time-invariant local labor market conditions, potentially related to the industry mix of the regions. By controlling for these factors, we look at individual differences within regions for a same family type.

For the exit rate regressions, we include an indicator for whether the individual is in a part-time job to account for the higher probability of exit from such jobs. In addition, we include the industry of the individual as an additional control variable. Controlling for industry information is important, as previous studies found that it is an important source of the difference of labor market outcomes among workers, such as gender gap (e.g., Blau and Kahn, 2017). Other control variables include family type and regions. By controlling for these factors, we look at individual differences within a region and an industry for a same family and occupational type.

For a robustness check to Equation 1, we also examine Equation 2, which includes time fixed effects instead of an aggregate cyclical indicator, for both job finding and exit rates

$$\Pr\left(Y_{i,t} = 1 | X_{i,t}, Z_{i,t}, G_t\right) = \Phi(\alpha + \beta X_{i,t} + \gamma Z_{i,t} + \delta_t + \epsilon_{i,t}). \quad (2)$$

This specification controls for the aggregate business cycle as well as other time-variant aggregate factors. By including time fixed effects, this specification will look at cross sectional differences of individuals.[6]

B. Results of Micro-level Regressions

Tables 2 and 3 report results of the probit regression for job finding and job exit rates respectively, with column 1, 2, and 3 showing coefficients based on the broad sample (which includes NILF) with different specifications while column 4, 5, and 6 showing coefficients for the narrow sample. The rows report the difference between the job-finding or separation rates of the group in question compared to the excluded group (mentioned in the first column of the table).

[5] In the HLFS, and individual can identify with more than one ethnicity. As is the convention when using ethnicity data from the HLFS, we do not include ethnicity as a pure categorical variable with one excluded group as this would require classifying each individual into prioritized ethnicity. Instead, we simply include 4 different multiple-response ethnicity dummies in our regression.

[6] Quarter fixed effects to control for seasonality are excluded in Equation 2, as they overlap with time fixed effects.

As discussed below, we find a significant role of individual characteristics, including gender, age, ethnicity, and education for both job finding rates and separation rates. The results are broadly similar for the narrow and broad samples, although they sometimes show different results for some characteristics, including gender and age, reflecting the difference in patterns of job exit and retirement decisions.

Gender: As shown in Table 2, after controlling for other factors, the job finding rate for women is somewhat lower than that for men (about 1 percentage point lower[7]) for the broad sample across specifications, although the difference is insignificant for the narrow sample. For job-exit rates, women have a higher probability of exiting from employment to unemployment or out of the labor force (broad sample, Table 3 columns 1-3). Interestingly, for the narrow sample, women have a slightly lower job exit rate than men. The difference in results between the two samples indicate that when women exit employment, they are more likely to exit the labor force than transition into unemployment. Likewise, women are not at a disadvantage compared to men when they are looking for work from a position of unemployment but are less likely to find employment from out of the labor force. This could be either because they find it harder to find a job after a stint out of the labor force (for example, after a maternity break) or because they are less likely to seek employment (potentially voluntarily) from out of the labor force.

Age: Next, we look at how finding and exit rates differ by age cohorts. Compared to the youth (15 to 24 year olds, who are the reference group in the regressions), other age groups have significantly lower exit rates, both for the narrow and broad sample. For the narrow sample which excludes exits out of the labor force, the oldest age cohort (55 to 64 years olds) has the lowest exit rate, while prime age workers (40-54 years olds) have the lowest exit rates for the broad sample. This difference reflects retirement decisions of the older age cohort, who are more likely to exit out of the labor force when they quit jobs.

The difference in job finding rates between the youth and prime age workers is relatively small in magnitude and often insignificant, indicating that while young workers tend to have more frequent job exit after controlling for other factors such as type of jobs, they tend to find jobs relatively quickly. Older worker have lower job finding rates for both the narrow and broad samples, indicating that their age can be a disadvantage in finding a new job after controlling for other factors.[8] This result is consistent with Barnichon and Figura (2015), which also find that lower job finding rates for older workers using U.S. CPS micro data over 1976-2012.

Ethnicity: Turning to ethnicities, as reported in Tables 2 and 3, we find that Māori and Pacific people tend to have both higher job exit rates as well as lower job finding rates, both for the broad and narrow samples, after controlling for other factors such as age, education and type of jobs. Europeans tend to have significantly lower job separation rates for all specifications and higher job finding rates for some specifications, too.

Education: The level of education is an important driver of labor market dynamics. Compared to individuals who have not graduated high school (the reference group in the regressions), people with higher levels of education have lower job exit rates and higher finding rates as reported in Tables 2 and 3. Furthermore, the finding rate increases monotonically with the level of education, for both the broad and narrow samples. For the

[7] Table 2 and 3 report raw coefficients from the probit model. These coefficients can be converted to marginal effects which account for the non-linearity of the probit model.

[8] The results for age are consists with Gorry (2013), who argues that experienced workers tend to have lower finding and separation rates.

broad sample, people with bachelor's degrees have almost twice as high a finding rate and 20 percent lower separation rate compared to individuals who have only completed high school.

Other determinants of job finding rates: In addition to the demographic characteristics explored above, the finding rate also depends crucially on the unemployment duration after controlling for other factors, both for the narrow and broad sample, consistent with Barnichon and Figura (2015) and Anand and others (2016). People who have been unemployed for more than a year have a finding rate that is about 17 percentage points lower than those unemployed for less than a year. This indicates potential scarring from long spells of unemployment. New entrants into the labor market who have never been employed also have a finding rate that is about 14 percentage points lower than those unemployed for less than a year. Also not surprisingly, for the broader sample, the finding rate is lower for people out of the labor force compared to those that are unemployed and actively looking for a job. On family type, single parents tend to have lower job finding rates both for the narrow and broad samples even after controlling for other factors such as ethnicity, age, gender and education.

Other determinants of job exit rates: Consistent with previous studies such as Farber (1999), whether a person is in a full time or part-time job significantly impacts exits rates. People with part time jobs are two and a half times more likely to transition to unemployment or out of the labor force compared to those with full-time jobs. On family type, single parents tend to have higher separation rates both for the narrow and broad samples even after controlling for other factors such as ethnicity, age, gender and education. On type of jobs included in the separation regressions, unskilled laborers and community and personal services tend to have higher exit rates compared to managers and professionals. On industry type, government and health jobs tend to have lower exit rates, while some services such as rental and real estate, and administrative support services tend to have higher exit rates.[9]

C. Methodology: Counterfactual Analysis for Steady State Unemployment Rates

Having documented how the job-finding rate and job-exit rate differ at the individual level based on individual characteristics, we next turn to some partial equilibrium calculations to quantify the macro effects of these different job-finding and exit rates on the unemployment rate of groups. In this decomposition exercise, we use group-specific finding rates from the regressions described above.[10] This approach differs from simply using raw job-finding and exit rates of each worker group as it quantifies the marginal impact of each characteristic after controlling for other factors.

We follow Shimer (2005, 2012), who shows that the non-employment/unemployment rate of a group in steady state can be approximated by the job finding rates and job exit rates (Equation 3):[11]

$$u_i \approx \frac{s_i}{s_i + f_i} \qquad , (3)$$

[9] While our sample includes the initial phase of the COVID crisis, our results are broadly similar if we exclude the COVID period.

[10] While the tables only report the marginal effect relative to a base group, the same regression can be used to calculate the level of the average finding and separation rate for each group at the average level (or integrating over) of all other covariates.

[11] Note that the focus of our analysis differs from Shimer (2012). While Shimer (2012) focuses on the extent to which variation in aggregate finding and separation rates over time contribute to fluctuations in unemployment rates, we instead focus on how differences in average transition probabilities across groups translate into variation in steady state unemployment rate for these groups.

where u_i denotes group *i's* steady state non-employment/unemployment rate, s_i denotes the job separation rate and f_i denotes the job finding rate of group *i*.[12]

We use this relationship to quantify the contribution of job-finding rates and separation rates to heterogeneity in steady state non-employment rates among worker groups.[13] In particular, we use the equation to construct counterfactual steady state non-employment/unemployment rates by changing either the finding rate or the separation rate of a group to that of another group. For example, consider the case of women with finding and separation rates of f_f and s_f. We compute the impact of differences in finding rate between women and men on the non-employment/unemployment using a conditional finding rate of male, f_m, which reflects marginal effects of being male after controlling for other factors:

$$u_f - u_f^{c,finding} \approx \frac{s_f}{s_f + f_f} - \frac{s_f}{s_f + \boldsymbol{f_m}} \qquad ,(4)$$

where $u_f = \frac{s_f}{s_f+f_f}$ is the steady state non-employment/unemployment rate for women implied by their finding and separation rate while $u_f^{c,finding} = \frac{s_f}{s_f+\boldsymbol{f_m}}$ is the counterfactual non-employment/unemployment rate for women if they had the finding rate of men.[14] Similarly, impact of differences in separation rates between women and men on the non-employment/unemployment rate of women is given by

$$u_f - u_f^{c,separation} \approx \frac{s_f}{s_f + f_f} - \frac{\boldsymbol{s_m}}{\boldsymbol{s_m} + f_m} \qquad ,(5)$$

D. Results of Counterfactual Analysis

Tables 4 and 5 report results for the counterfactual exercise described above for the broad and narrow samples, respectively.

Overall, we find that higher separation rates of young workers play a disproportionate role in explaining heterogeneity of employment outcomes across age groups, while differences in finding rates are somewhat more important in explaining differences by education level. Both finding and separation rate differences are important in explaining differences across ethnicities.

Gender: The first row of Table 4 shows the results for the counterfactual exercise for females versus males, based on parameters reported in Column 1 of Tables 2 and 3, which are estimated from the broad sample. Column 1 reports that the non-employment rate in the data is 10 percentage points higher for women compared to men. The lower finding rate for women (after controlling for other observables) only explains 1.2

[12] Using the average aggregate job finding and separation rate over our entire sample with equation 3 yields a steady state unemployment rate of about 3.6 percent, which is below the average for this period (about 5 percent), but close to the actual unemployment rate towards the end of our sample. The discrepancy between the implied steady state unemployment rate from equation 3 and the actual average over the sample may reflect the fact that our sample is relatively short, encompasses two recessions, and significant shifts in the finding rate (see Figure 2), making the steady state calculation less precise.

[13] For the analysis on the unemployment rate, we ignore movements in and out of the labor force as Shimer (2012) does in his benchmark excise. Shimer (2012) finds that this does not affect his main findings for the US data.

[14] It should be noted that $f_m$is not the raw finding rate of men, but rather the conditional finding rate at the average level (or integrating over) of all other covariates based on the regressions described in the previous section.

percentage points of this difference (column 2), reflecting the relatively small difference in finding rate between the men and women. On the other hand, the higher separation rate of women (after controlling for other characteristics) accounts for 3.8 percentage points of the difference in their non-employment rates. Note that 5.7 percentage points of the difference in non-employment is not explained by the marginal effect of gender on finding or separation rates. This suggests that more than half of the gender difference is explained by other factors incorporated in the regressions in Tables 2 and 3. For example, women may be more likely to work part time or in less stable occupation with high separation rates.[15]

The first row of Table 5 shows the results for the counterfactual exercise for females versus males based on the narrow sample. For the narrow sample, the difference in the unemployment rates is much smaller because they do not account for a larger share of female workers not in the labor force. As women do not have very different job finding and separation rates than men in the narrow sample, these cannot explain the gap in unemployment rates between men and women. Like non-employment rate in Table 4, other factors that are controlled for in the regression, like a higher share of part-time jobs for female workers, may explain the difference in the unemployment rates across men and women.

Age: The counterfactual exercise in Table 4 confirms the relatively larger importance of exit rates in explaining differences in the non-employment rate across age cohorts. The table compares different age cohorts to 40 to 54 year olds (who have the lowest non-employment in the data). The non-employment rate for youth (15 to 24 year olds) is more than 30 percentage points higher than 40 to 54 year olds, with higher separation rate explaining more than half of the difference. For 25 to 39 year olds, the higher separation rate explains the entire difference in non-employment rate compared to 40 to 54 year olds. The pattern is different for the older age cohort (55 to 64), where both lower finding and higher separation play an important role.

Table 5 analyzes the drivers of the unemployment rate differences based on the counterfactual exercise with the narrow sample. Similar to Table 4, for workers aged 15-24 and 25-39, job separation rates drive the differences relative to workers aged 40-54, although the differences are much smaller than the non-employment rates based on the broad sample. Similarly, for workers aged 55-64, the difference relative to workers aged 40-54 is much smaller for the unemployment rates.

Ethnicity: The results for the counterfactual exercise in Table 4 show that both finding and exit rates are quantitatively important in explaining the higher non-employment rates for both groups. The non-employment rate for Māori is 10.8 percentage points higher than for non-Māori. About 3.8 percentage points can be explained by the lower finding rates for Māori and a further 3.6 percentage points is explained by their higher separation rate. However, a significant difference in the non-employment rate for Māori is not explained by the differences in finding and separation rates due to ethnicity-specific factors, likely reflecting the fact Māori also have other characteristics that are associated with lower finding or higher separation rates that are controlled for in the regressions in Tables 2 and 3. For example, Māori may be more likely to work part time. Other factors, such as age distribution and the difference in qualification levels may also be contributing.[16] A similar pattern is seen for Pacific people. For other non-European ethnicities, finding rates are lower but there is no

[15] The part-time employment-to-labor force ratio for female workers is, on average, 20 percentage points higher than that for male workers for the sample period.

[16] Youth population accounts for 30.2 percent and 31.7 percent of working age population of Māori and Pacific people, respectively, while it only accounts for 19.9 percent of working age population of European people. As Theodore et al, (2018) discuss, the share of people with bachelor's degree or higher degrees is lower for Māori and Pacific people compared to other people.

large difference in exit rates compared to other ethnicities. As shown in Table 4, the non-employment rate for Others is about 4 percentage points higher, most of which is explained by the lower finding rate.

Table 5 shows the differences in the unemployment rates based on the narrow sample. Similar to Table 4, higher unemployment rates for Māori and Pacific people are explained partially by the job finding rates and separation rates, although other factors are also contributing to the differences.

Education: The counterfactual exercise in Table 4 displays the relatively larger importance of finding rates in explaining differences in the non-employment rates across different qualifications. The Table compares different qualification groups to the group that has not graduated high school (the lowest qualification). The non-employment rate for the group with bachelor's degree is 27.6 percentage points lower than the lowest qualification group, with the higher job finding rate explaining 8.8 percentage points of the difference and the lower separation rate explaining 3.6 percentage points of the difference. That said, about half of the difference is not explained by education level, and other factors, such as the share of part-time employment, age distribution, ethnicity, and industry also play a role. Similarly, for the groups with post-secondary degree and secondary school education, the large differences with the group with lowest qualifications are explained by their higher job finding rates and lower separation rates, while other factors also contribute to the differences.

Table 5 shows the differences in the unemployment rates based on the narrow sample. Similar to Table 4, job finding rates explain a larger part of the differences, except for the group with secondary school education.

4. Heterogenous Response to Business Cycles

Equation 1 abstracts from the potential heterogenous responses of finding and exit rates of groups to business cycles. In this section, we analyze how labor flows of different worker groups behave in response to business cycles using Equation 6, which expands the benchmark regression.

$$\Pr\left(Y_{i,t} = 1 | X_{i,t}, Z_{i,t}, G_t\right) = \Phi(\alpha + \beta X_{i,t-1} + \gamma Z_{i,t-1} + \sigma G_t + \lambda X_{i,t} * G_t + \epsilon_{i,t}) \quad ,(6)$$

where $X_{i,t} * G_t$ is a vector of interaction terms of dummies for individual characteristic terms and the business cycle indicator (annual per capita GDP growth rate or output gap). With this specification, parameter λ captures heterogenous responses of worker groups to business cycles, and parameter β gauges time-invariant heterogeneity after controlling for cyclical heterogeneity.

Tables 6 and 7 report the estimated parameters for Equation (6) with regard to job finding and separation rates, focusing on parameters associated with the business cycle interacted with individual characteristics (λ). They show some heterogeneity in job finding and separation rates.[17]

With regard to age, we find that job finding rates for young workers are more cyclical while job finding rates for older workers at 55-64 are least cyclical. On job separation, although the difference is smaller, prime age workers and, for some specifications, older workers aged at 55-64 tend to have more cyclical exit rates. This

[17] For robustness checks on the results in Section III, we report the parameters for time-invariant individual characteristics in Appendix Tables 1 and 2. The results in Section III are robust to the addition of the interaction terms of business cycle indicators and individual characteristics.

finding is consistent with Gielen and Ours (2006), which find that cyclical adjustment of the workforce occurs mainly through fluctuations in worker entry for young workers, while it occurs through fluctuations in separations for old workers. On ethnicity, Māori and Pacific people tend to have more procyclical job finding rates compared to European people and other ethnic groups for the broad sample after controlling for other factors, while there are no significant differences in cyclicality of job exit rates. On qualification, workers who have only completed high school tend to have more cyclical job exit rates, while there are no large differences in job finding rates. These findings are similar to findings by Hoynes and others (2012) for the U.S. labor market, who find that non-European people and lower-education workers tend to suffer more during recessions. For New Zealand's labor market, we find that job exit rates explain the difference in cyclicality by age groups and job finding rates explain the difference in cyclicality by ethnicity. On gender, while some previous studies find that the male unemployment rate tend to be less cyclical (e.g., Zanin, 2014), we do not find significant differences after controlling for other factors.

5. Conclusion

In this paper, we explore the sources of difference in unemployment rates for different groups, focusing on age, gender, ethnicity, and qualification. In doing so, we focus on New Zealand labor market data and use novel anonymized individual-level Household Labour Force Survey data. We include rich set of control variables and analyze the impact of individual characteristics within region, industry, and type of jobs (full-time or part-time). We decompose the unemployment rates into gross flows and examine the contribution of job finding rates and separation rates to the differences in the unemployment rates among workers by calculating the marginal impact of individual characteristics on job finding and separation rates. We also investigate heterogeneity of individuals' responses to cyclical fluctuations.

We find a significant role of individual characteristics in explaining job finding and separation probabilities. Our unemployment rate decomposition exercise finds important sources of differences in the unemployment rates. On differences among age groups, the higher separation rate of young workers explains the larger part of the unemployment rate gap between youth and prime age workers, while lower job finding probabilities of older workers also explain the gap between workers aged 55-64 and younger prime age workers. On gender and ethnicity gaps, we also find that the higher separation rate of female, Māori, and Pacific workers plays a large role, while the difference in finding rates between non-European and European workers also contributes to some of ethnicity gap.

We conduct our analysis for two samples, for the narrow sample which focuses on transitions into and out of unemployment for people in the labor force, as well as for the broad sample which also includes transitions into and out of the labor force. Results are broadly similar for the two samples, though they differ for some characteristics. In particular, while finding rates for women are similar to men for the narrow sample, they are significantly lower for the broad sample, indicating that women are less likely than men to transition from out of the labor force to employment. Also, for the narrow sample, the oldest age cohort (55 to 64 years olds) has the lowest exit rate, while the prime age workers (40-54 years olds) have the lowest exit rates for the broad sample. This difference reflects retirement decisions of the older age cohort, who are more likely to transition from employment to out of the labor force than into unemployment.

Our results are robust to alternative specifications, which control for heterogenous responses to business cycle. We also find some cyclical heterogeneity among individuals; youth workers, Māori and Pacific people tend to have more cyclical job finding rates after controlling for other factors; older workers aged at 55-64 and workers with high school education tend to have more cyclical job exit rates.

Our results have important policy implications. The larger role of job separation rates in explaining higher non-employment rates for youth workers and female suggests that labor market policies that support job entry may not be sufficient to address youth unemployment and gender gaps in the labor market, and policies that support longer employment duration such as training would be important.[18] At the same time, the larger contribution of job finding rates in higher non-employment rates for older workers, Māori and Pacific people suggests that labor market policies that support job finding, such as job search assistance and targeted hiring credits, remain important. More cyclical behavior of some worker groups, especially young, Māori, and Pacific workers, suggests that the sufficient coverage of income insurance for them would be essential to promote economic stability, and intensified labor market policies targeted to these groups during downturns would be warranted.[19]

[18] Several studies have found that training programs would increase duration of employment, in addition to reducing unemployment duration. For example, Gritz (1993) argues that participation in a private training program would increase duration of employment spells. Fitzenberger and others (2013) find that training programs that teach new skills have better results than programs that train for job readiness in increasing employment duration.

[19] For example, Cahuc and others (2019) argue that temporary hiring credit introduced during recessions would have significant positive employment effects.

Figure 1. Unemployment Rate, New Zealand

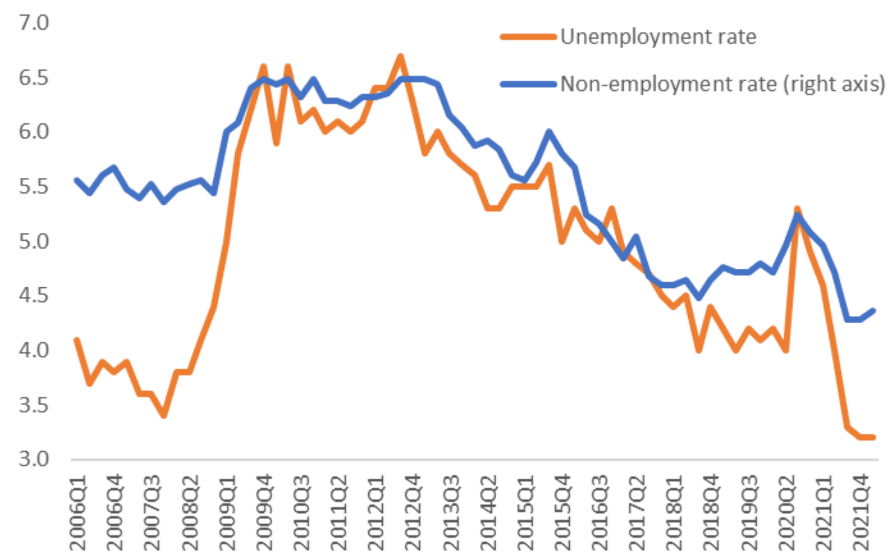

Figure 2. Job-finding and Job-separation Rate, 4 Quarter Moving Average, New Zealand

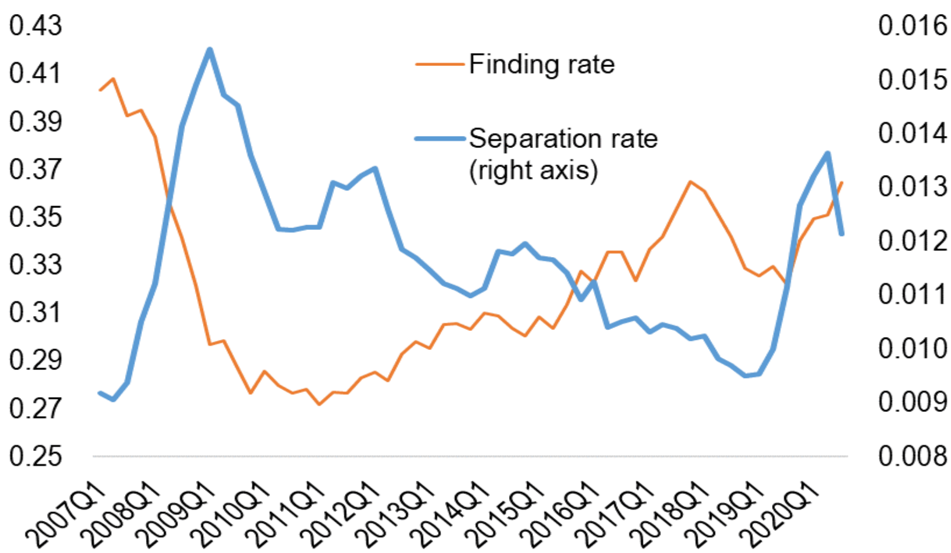

Table 1. Labor Market Indicators of Worker Groups

	Non-employment rate	(difference with total)	Unemployment rate	(difference with total)
Total	25.4	---	5.3	---
Gender: Male	19.9	-5.5	5.0	-0.3
Gender: Female	30.4	5.0	5.6	0.2
Age: 15-24	46.8	21.4	13.6	8.2
Age: 25-39	20.1	-5.3	4.5	-0.8
Age: 40-54	15.9	-9.5	3.2	-2.1
Age: 55-64	25.1	-0.3	2.9	-2.4
Ethnicity: European	21.3	-4.1	4.2	-1.2
Ethnicity: Māori	36.6	11.2	11.3	6.0
Ethnicity: Pacific	40.3	14.9	11.2	5.9
Ethnicity: Others	29.8	4.4	5.8	0.4
Education: Bachelor and above	13.1	-12.3	2.6	-2.7
Education: Post secondary school	16.6	-8.8	3.8	-1.5
Education: Secondary school	29.9	4.5	6.2	0.9
Education: All lower	40.6	15.3	7.6	2.3

Note: The table reports the non-employment rate and the unemployment rate for different worker groups (in percent), and their deviation from total workers aged 15-64 based on the sample from 2006Q1 to 2021Q1. The non-employment rate is defined as the share of the population that is either unemployed or not in the labor force.

Table 2. Job-finding Regressions: Probit Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Broad	Broad	Broad	Narrow	Narrow	Narrow
Not in labour force	-0.540***	-0.537***	-0.545***	--	--	--
	(0.010)	(0.010)	(0.010)			
Age (15 to 24)						
25-39	0.00384	0.0037	0.00738	-0.000492	0.00102	0.000979
	(0.013)	(0.013)	(0.013)	(0.025)	(0.025)	(0.025)
40-54	-0.0329**	-0.0341**	-0.0282**	-0.033	-0.0366	-0.0319
	(0.014)	(0.014)	(0.014)	(0.025)	(0.025)	(0.025)
55-64	-0.264***	-0.264***	-0.255***	-0.264***	-0.265***	-0.263***
	(0.017)	(0.017)	(0.017)	(0.033)	(0.033)	(0.033)
Ethnicity						
European	0.00664	-0.0162	0.0848***	0.0744***	0.031	0.0991***
	(0.014)	(0.013)	(0.017)	(0.027)	(0.026)	(0.032)
Māori	-0.126***	-0.140***	-0.0738***	-0.143***	-0.173***	-0.126***
	(0.014)	(0.014)	(0.015)	(0.026)	(0.025)	(0.028)
Pacific	-0.133***	-0.151***	-0.0626***	-0.139***	-0.174***	-0.115***
	(0.018)	(0.018)	(0.020)	(0.034)	(0.033)	(0.037)
Asian and Others	-0.124***	-0.147***	-0.0386*	-0.0675*	-0.111***	-0.0389
	(0.018)	(0.018)	(0.021)	(0.035)	(0.035)	(0.039)
Gender (Male)						
Female	-0.0474***	-0.0475***	-0.0489***	0.0188	0.0194	0.0166
	(0.009)	(0.009)	(0.009)	(0.017)	(0.017)	(0.017)
Education (Primary or less)						
Bachelor and above	0.376***	0.378***	0.381***	0.397***	0.403***	0.401***
	(0.015)	(0.015)	(0.015)	(0.030)	(0.030)	(0.030)
Post-school	0.239***	0.238***	0.238***	0.197***	0.191***	0.201***
	(0.014)	(0.014)	(0.014)	(0.025)	(0.025)	(0.025)
High-school	0.184***	0.186***	0.189***	0.131***	0.135***	0.133***
	(0.011)	(0.011)	(0.011)	(0.023)	(0.023)	(0.023)
Unemployment duration (Unemployed>=1yr)						
Never worked	0.192***	0.193***	0.193***	0.0741***	0.0814***	0.0747***
	(0.013)	(0.013)	(0.013)	(0.028)	(0.028)	(0.028)
Unemployed < 1 year	0.705***	0.707***	0.708***	0.597***	0.608***	0.599***
	(0.011)	(0.011)	(0.011)	(0.020)	(0.020)	(0.020)
Output gap	0.0185***	--	--	0.0510***	--	--
	(0.003)			(0.006)		
GDP growth	--	0.00154	--	--	0.0121***	--
		(0.002)			(0.004)	
Constant	-0.972***	-0.967***	-1.177***	-0.881***	-0.909***	-0.888***
	(0.027)	(0.027)	(0.053)	(0.047)	(0.049)	(0.107)
Time fixed effects	No	No	Yes	No	No	Yes
Observations	242,289	242,289	242,289	37,812	37,812	37,812
R2	0.107	0.107	0.109	0.0709	0.0693	0.0726

Note: The table reports the parameters for Equation 1 and 2 regarding job finding rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, the regressions also include seasonal dummies, regional council dummies, household type. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively.

Table 3. Job-exit Regressions: Probit Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Broad	Broad	Broad	Narrow	Narrow	Narrow
Part-time	0.595***	0.596***	0.594***	0.331***	0.333***	0.333***
	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)	(0.014)
Age (15 to 24)						
25-39	-0.299***	-0.299***	-0.299***	-0.256***	-0.255***	-0.258***
	(0.011)	(0.011)	(0.011)	(0.017)	(0.017)	(0.017)
40-54	-0.466***	-0.463***	-0.467***	-0.319***	-0.315***	-0.321***
	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)
55-64	-0.359***	-0.357***	-0.354***	-0.378***	-0.376***	-0.381***
	(0.013)	(0.013)	(0.013)	(0.020)	(0.020)	(0.020)
Ethnicity						
European	-0.154***	-0.126***	-0.143***	-0.105***	-0.0697***	-0.150***
	(0.012)	(0.011)	(0.016)	(0.016)	(0.015)	(0.021)
Māori	0.0811***	0.0967***	0.0918***	0.156***	0.176***	0.128***
	(0.012)	(0.011)	(0.013)	(0.016)	(0.016)	(0.019)
Pacific	0.0822***	0.102***	0.0965***	0.128***	0.153***	0.0908***
	(0.017)	(0.016)	(0.019)	(0.023)	(0.022)	(0.026)
Others	-0.0149	0.0128	0.00375	-0.0149	0.0195	-0.0606**
	(0.015)	(0.014)	(0.018)	(0.021)	(0.020)	(0.026)
Gender (Male)						
Female	0.111***	0.111***	0.112***	-0.0531***	-0.0537***	-0.0533***
	(0.009)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)
Education (Primary or less)						
Bachelor and above	-0.119***	-0.123***	-0.111***	-0.0408**	-0.0466**	-0.0408**
	(0.013)	(0.013)	(0.013)	(0.020)	(0.020)	(0.020)
Post-school qualification	-0.109***	-0.111***	-0.110***	-0.0462***	-0.0474***	-0.0455***
	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)
secondary qualification	-0.0834***	-0.0857***	-0.0736***	-0.0839***	-0.0869***	-0.0829***
	(0.010)	(0.010)	(0.010)	(0.016)	(0.016)	(0.016)
Output gap	-0.0273***	--	--	-0.0373***	--	--
	(0.003)			(0.004)		
GDP growth	--	-0.0137***	--	--	-0.0172***	--
		(0.001)			(0.002)	
Constant	-1.251***	-1.230***	-1.337***	-1.883***	-1.857***	-1.971***
	(0.026)	(0.027)	(0.048)	(0.039)	(0.040)	(0.075)
Time fixed effects	No	No	Yes	No	No	Yes
Observations	736,551	736,551	736,551	713,115	713,115	713,115
R2	0.1	0.0999	0.102	0.0682	0.0678	0.07

Note: The table reports the parameters for Equation 1 and 2 regarding job separation rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, the regressions also include seasonal dummies, regional council dummies, household type, part-time job dummies, and sectors. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively.

Table 4. Decomposition of Steady State Non-employment Rates

	(1) Difference in data	(2) Difference due to finding rate	(3) Difference due to separation rate	(4) Difference from both	(5) Unexplained difference
Gender					
Female minus Male	10.5	1.2	3.8	4.8	5.7
Age					
Youth (15-24) minus 40 to 54	31.0	-1.0	15.9	15.3	15.7
25 to 39 minus 40 to 54	4.2	-0.8	5.0	4.4	-0.2
55 to 64 minus 40 to 54	9.2	5.9	4.0	9.1	0.1
Ethnicity					
European minus Others	-4.4	0.4	-4.3	-3.8	-0.6
Māori minus Others	10.8	3.8	3.6	7.1	3.8
Pacific people minus Others	14.5	4.3	3.9	7.8	6.7
Other non-European minus Others	4.0	3.8	0.5	4.2	-0.2
Education					
Bachelors minus low	-27.6	-8.8	-3.6	-13.6	-14.0
Post school minus low	-24.1	-6.1	-3.6	-10.4	-13.7
Secondary school minus low	-10.8	-5.1	-3.0	-8.4	-2.4

Note: The table reports the decomposition of differences in steady state non-employment rate (unemployment and non-in-labor-force rates) for the selected worker groups based on Equations 4 and 5 (broad samples). Differences due to finding and separation rates are derived from the parameters reported in Tables 2 and 3, therefore capture marginal effects of the differences in individual characteristics after controlling for other factors. Units are in percentage points.

Table 5. Decomposition of Steady State Unemployment Rates

	(1) Difference in data	(2) Difference due to finding rate	(3) Difference due to separation rate	(4) Difference from both	(5) Unexplained difference
Gender					
Female minus Male	0.6	-0.1	-0.5	-0.5	1.1
Age					
Youth (15-24) minus 40 to 54	10.3	-0.2	3.1	3.0	7.3
25 to 39 minus 40 to 54	1.2	-0.1	0.5	0.3	0.9
55 to 64 minus 40 to 54	-0.4	0.7	-0.5	0.3	-0.6
Ethnicity					
European minus Others	-1.6	-0.1	-0.6	-0.7	-0.9
Māori minus Others	5.5	0.9	1.9	2.6	3.0
Pacific people minus Others	5.4	1.0	1.7	2.4	3.0
Other non-European minus Others	0.0	0.4	0.2	0.6	-0.6
Education					
Bachelors minus low	-5.0	-1.4	-0.3	-1.9	-3.0
Post school minus low	-3.8	-0.8	-0.4	-1.3	-2.5
Secondary school minus low	-1.4	-0.5	-0.8	-1.4	0.1

Note: The table reports the decomposition of differences in steady state unemployment rate for the selected worker groups based on Equations 4 and 5 (narrow samples). Differences due to finding and separation rates are derived from the parameters reported in Tables 2 and 3, therefore capture marginal effects of the differences in individual characteristics after controlling for other factors. Units are in percentage points.

Table 6. Job-finding Regressions with Business Cycle Interaction Terms

	(1)	(2)	(3)	(4)
Sample	Braod	Broad	Narrow	Narrow
Cyclical Indicator × Age (15 to 24)				
25-39	-0.0223**	-0.0165***	-0.0556***	-0.0262**
	(0.009)	(0.006)	(0.017)	(0.011)
40-54	-0.0278***	-0.0203***	-0.0469***	-0.0155
	(0.009)	(0.006)	(0.017)	(0.011)
55-64	-0.0417***	-0.0225***	-0.0696***	-0.0434***
	(0.011)	(0.006)	(0.023)	(0.013)
Cyclical Indicator × Gender (Male)				
Female	-0.00783	0.001	0.0066	0.00259
	(0.006)	(0.004)	(0.012)	(0.008)
Cyclical Indicator × Ethnicity				
European	-0.0490***	-0.0177***	-0.023	-0.00427
	(0.008)	(0.007)	(0.016)	(0.013)
Māori	-0.0033	-0.00836	0.023	0.000692
	(0.009)	(0.006)	(0.017)	(0.012)
Pacific	-0.0102	-0.0121	-0.00393	0.00443
	(0.012)	(0.008)	(0.023)	(0.016)
Others	-0.0343***	-0.0183**	-0.00816	-0.013
	(0.012)	(0.008)	(0.023)	(0.016)
Cyclical Indicator × Education (Primary or less)				
Bachelor and above	0.00373	0.00718	0.028	0.0350***
	(0.010)	(0.006)	(0.021)	(0.013)
Post-school	0.0208**	0.00406	0.0151	0.0105
	(0.009)	(0.006)	(0.017)	(0.011)
High-school	0.0119	0.0048	0.00858	0.0152
	(0.007)	(0.005)	(0.016)	(0.011)
Cyclical Indicator × Unemployment Duration (Unemployed>=1yr)				
Never worked	0.0126	-0.0124**	0.0104	0.0113
	(0.009)	(0.006)	(0.020)	(0.015)
Unemployed < 1 year	-0.00603	-0.00409	0.000887	0.0079
	(0.007)	(0.005)	(0.014)	(0.009)
Output gap	0.0622***	--	0.0740***	--
	(0.012)		(0.023)	
GDP growth	--	0.0305***	--	0.00957
		(0.009)		(0.019)
Constant	-0.994***	-1.038***	-0.881***	-0.903***
	(0.028)	(0.035)	(0.049)	(0.065)
Observations	242,289	242,289	37,812	37,812
R2	0.108	0.107	0.0718	0.07

Note: The table reports the parameters of interaction terms in Equation 6 regarding job-finding rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, time-invariant variables shown in Table 2 are also included. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively.

Table 7. Job-exit Regressions with Business Cycle Interaction Terms

	(1)	(2)	(3)	(4)
Sample	Braod	Broad	Narrow	Narrow
Cyclical Indicator × Age (15 to 24)				
25-39	-0.0139*	-0.00111	-0.0388***	-0.00039
	(0.007)	(0.004)	(0.011)	(0.006)
40-54	-0.0162**	-0.00713*	-0.0426***	-0.0103*
	(0.007)	(0.004)	(0.011)	(0.006)
55-64	-0.00883	-0.00015	-0.0390***	-0.00508
	(0.008)	(0.004)	(0.013)	(0.007)
Cyclical Indicator × Gender (Male)				
Female	0.00555	4.95E-07	0.0102	-0.00314
	(0.005)	(0.003)	(0.008)	(0.004)
Cyclical Indicator × Ethnicity				
European	-0.00579	-0.00149	-0.00038	-0.00342
	(0.006)	(0.003)	(0.009)	(0.005)
Māori	-0.0119	0.00144	0.0178	0.0135**
	(0.008)	(0.004)	(0.011)	(0.006)
Pacific	-0.00943	-0.00194	-0.00425	0.00215
	(0.011)	(0.005)	(0.015)	(0.008)
Others	0.00722	-0.0233***	0.0681***	-0.00852
	(0.019)	(0.008)	(0.025)	(0.012)
Cyclical Indicator × Education (Primary or less)				
Bachelor and above	-0.00827	-0.00024	-0.0112	-0.00262
	(0.008)	(0.004)	(0.012)	(0.006)
Post-school	-0.00997	-0.0043	-0.0296***	-0.00658
	(0.007)	(0.004)	(0.010)	(0.006)
High-school	-0.0144**	0.00166	-0.0306***	0.00141
	(0.007)	(0.004)	(0.011)	(0.006)
Output gap	-0.00581		0.00368	
	(0.009)		(0.013)	
GDP growth		-0.00945*		-0.0099
		(0.005)		(0.007)
Constant	-1.252***	-1.240***	-1.866***	-1.870***
	(0.027)	(0.029)	(0.040)	(0.043)
Observations	736,551	736,551	713,115	713,115
R2	0.100	0.100	0.069	0.068

Note: The table reports the parameters of interaction terms for Equation 6 regarding job-separation rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, time-invariant variables shown in Table 3 are also included. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively..

Appendix 1. Robustness Checks

Appendix Table 1. Job-finding Regressions: Probit Regression (Robustness Checks)

	(7)	(8)	(9)	(10)
Sample	Braod	Broad	Narrow	Narrow
Not in labour force	-0.541***	-0.537***	--	--
	(0.010)	(0.010)		
Age (15 to 24)				
25-39	-0.00515	0.0378**	-0.0314	0.0566*
	(0.014)	(0.018)	(0.026)	(0.033)
40-54	-0.0436***	0.00813	-0.0599**	-0.0043
	(0.015)	(0.018)	(0.026)	(0.034)
55-64	-0.279***	-0.217***	-0.304***	-0.175***
	(0.018)	(0.021)	(0.036)	(0.043)
Ethnicity				
European	0.0169	0.0316	0.0698**	0.0419
	(0.015)	(0.022)	(0.028)	(0.043)
Māori	-0.100***	-0.115***	-0.119***	-0.173***
	(0.015)	(0.019)	(0.028)	(0.038)
Pacific	-0.102***	-0.116***	-0.133***	-0.182***
	(0.020)	(0.026)	(0.036)	(0.050)
Asian and Others	-0.101***	-0.0972***	-0.0581	-0.0803
	(0.019)	(0.026)	(0.036)	(0.053)
Gender (Male)				
Female	-0.0515***	-0.0497***	0.0228	0.0139
	(0.009)	(0.012)	(0.018)	(0.023)
Education (Primary or less)				
Bachelor and above	0.380***	0.363***	0.415***	0.328***
	(0.015)	(0.019)	(0.031)	(0.041)
Post-school	0.249***	0.229***	0.205***	0.168***
	(0.015)	(0.018)	(0.027)	(0.034)
High-school	0.192***	0.176***	0.136***	0.101***
	(0.011)	(0.015)	(0.024)	(0.032)
Unemployment duration (Unemployed>=1yr)				
Never worked	0.198***	0.218***	0.0766**	0.0504
	(0.014)	(0.018)	(0.030)	(0.044)
Unemployed < 1 year	0.702***	0.715***	0.597***	0.590***
	(0.012)	(0.015)	(0.022)	(0.028)
Output gap	0.0622***	--	0.0740***	--
	(0.012)		(0.023)	
GDP growth	--	0.0305***	--	0.00957
		(0.009)		(0.019)
Constant	-0.994***	-1.038***	-0.881***	-0.903***
	(0.028)	(0.035)	(0.049)	(0.065)
Time fixed effects	No	No	No	No
Observations	242,289	242,289	37,812	37,812
R2	0.108	0.107	0.072	0.070

Note: The table reports the parameters of workers' characteristics in Equation 6 regarding job finding rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, the regressions also include seasonal dummies, regional council dummies, household type, and the interaction terms reported in Table 6. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively.

Appendix Table 2. Job-exit Regressions: Probit Regression (Robustness Checks)

	(7)	(8)	(9)	(10)
Sample	Braod	Broad	Narrow	Narrow
Part-time	0.595***	0.597***	0.332***	0.333***
	(0.009)	(0.009)	(0.014)	(0.014)
Age (15 to 24)				
25-39	-0.304***	-0.297***	-0.273***	-0.254***
	(0.011)	(0.014)	(0.017)	(0.020)
40-54	-0.473***	-0.449***	-0.338***	-0.295***
	(0.012)	(0.014)	(0.017)	(0.020)
55-64	-0.361***	-0.356***	-0.395***	-0.366***
	(0.013)	(0.016)	(0.021)	(0.024)
Ethnicity				
European	-0.149***	-0.122***	-0.108***	-0.0643***
	(0.012)	(0.014)	(0.017)	(0.019)
Māori	0.0797***	0.0941***	0.166***	0.149***
	(0.013)	(0.014)	(0.017)	(0.020)
Pacific	0.0845***	0.107***	0.126***	0.148***
	(0.017)	(0.020)	(0.024)	(0.028)
Others	-0.00507	0.0191	-0.01	0.0206
	(0.016)	(0.015)	(0.023)	(0.021)
Gender (Male)				
Female	0.114***	0.111***	-0.0476***	-0.0476***
	(0.009)	(0.010)	(0.013)	(0.015)
Education (Primary or less)				
Bachelor and above	-0.123***	-0.124***	-0.0466**	-0.0421*
	(0.013)	(0.015)	(0.020)	(0.023)
Post-school qualification	-0.114***	-0.103***	-0.0616***	-0.0354*
	(0.011)	(0.013)	(0.017)	(0.019)
secondary qualification	-0.0894***	-0.0894***	-0.0985***	-0.0906***
	(0.011)	(0.013)	(0.017)	(0.020)
Output gap	-0.00581	--	0.00368	--
	(0.009)		(0.013)	
GDP growth	--	-0.00945*	--	-0.0099
		(0.005)		(0.007)
Constant	-1.252***	-1.240***	-1.866***	-1.870***
	(0.027)	(0.029)	(0.040)	(0.043)
Time fixed effects	No	No	No	No
Observations	736551	736551	713115	713115
R2	0.100	0.100	0.0689	0.0681

Note: The table reports the parameters of workers' characteristics in Equation 6 regarding job separation rates based on the sample from 2006Q1 to 2021Q1. In addition to the variables reported in the table, the regressions also include seasonal dummies, regional council dummies, occupational type, household type, industry, and the interaction terms reported in Table 7. Standard errors are clustered at individual level. *, **, and *** indicate significance at the 10, 5 and 1 percent level respectively.

References

Anand, R., Kothari, S., Kumar, N., & Papi, L. (2016). South Africa: Labor Market Dynamics and Inequality1. IMF Working Papers, *2016*(137).

Ahn, H. J., & Hamilton, J. D. (2020). Heterogeneity and unemployment dynamics. *Journal of Business & Economic Statistics*, *38*(3), 554-569.

Alesina, A., Algan, Y., Cahuc, P., & Giuliano, P. (2015). Family values and the regulation of labor. *Journal of the European Economic Association*, *13*(4), 599-630.

Altonji, J. G., & Blank, R. M. (1999). Race and gender in the labor market. Handbook of labor economics, 3, 3143-3259.

Baker, M., & Benjamin, D. (1997). The role of the family in immigrants' labor-market activity: an evaluation of alternative explanations. *American Economic Review*, 705-727.

Ball, C., Groshenny, N., Karagedikli, Ö., Ozbilgin, M., & Robinson, F. (2020). "Low Wage Growth and Job-to-job Transitions: Evidence from Administrative Data in New Zealand."

Barnichon, R., & Figura, A. (2015). Labor market heterogeneity and the aggregate matching function. *American Economic Journal: Macroeconomics*, *7*(4), 2

Blau, F. D., & Kahn, L. M. (2017). The Gender Wage Gap: Extent, Trends, and Explanations. *Journal of Economic Literature*, *55*(3), 789-865.

Cahuc, P., Carcillo, S., & Le Barbanchon, T. (2019). The effectiveness of hiring credits. *The Review of Economic Studies*, *86*(2), 593-626.

Choi, S., Janiak, A., & Villena-Roldán, B. (2015). Unemployment, Participation and Worker Flows Over the Life-Cycle. *The Economic Journal*, *125*(589), 1705-1733.

Clark, K. B., Summers, L. H., Holt, C. C., Hall, R. E., Baily, M. N., & Clark, K. B. (1979). Labor market dynamics and unemployment: a reconsideration. *Brookings Papers on Economic Activity*, *1979*(1), 13-72.

Elsby, M., Hobijn, B., and Sahin, A. (2013). Unemployment Dynamics in the OECD. *The Review of Economics and Statistics*, MIT Press 95 (2): 530-548.

Farber, H. S. (1999). Alternative and Part-time Employment Arrangements as a Response to Job Loss. *Journal of Labor Economics*, *17*(S4), 142-169.

Fitzenberger, B., Orlanski, O., Osikominu, A., & Paul, M. (2013). Déjà Vu? Short-term training in Germany 1980–1992 and 2000–2003. *Empirical Economics*, *44*(1), 289-328.

Fujita, S., & Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, *50*(2), 415-430.

Gielen, A. C., & van Ours, J. C. (2006). Age-specific cyclical effects in job reallocation and labor mobility. Labour Economics, 13(4), 493-504.

Gorry, A. (2013). Minimum Wages and Youth Unemployment. *European Economic Review*, *64*, 57-75.

Gritz, R. M. (1993). The impact of training on the frequency and duration of employment. *Journal of Econometrics*, *57*(1-3), 21-51.

Hall, Robert E. (2005). Employment Fluctuations With Equilibrium Wage Stickiness. *American Economic Review* 95(1): 50-65.

Hairault, J. O., Le Barbanchon, T., & Sopraseuth, T. (2015). The Cyclicality of the Separation and Job Finding Rates in France. *European Economic Review*, *76*, 60-84.

Hoynes, H., Miller, D. L., & Schaller, J. (2012). Who suffers during recessions?. *Journal of Economic Perspectives*, *26*(3), 27-48.

Hyslop, D., & Stillman, S. (2007). Youth minimum wage reform and the labour market in New Zealand. *Labour Economics*, *14*(2), 201-230.

Hyslop, D., Rice, A., & Skilling, H. (2019). *Understanding labour market developments in New Zealand, 1986-2017* (No. DP2019/02). Reserve Bank of New Zealand.

Jacob, P., & Robinson, F. (2019). "Suite as! Augmenting the Reserve Bank's output gap indicator suite," Reserve Bank of New Zealand Analytical Notes series AN2019/08, Reserve Bank of New Zealand.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, *95*(1), 25-49.

Shimer, R. (2012). Reassessing the ins and outs of unemployment. *Review of Economic Dynamics*, *15*(2), 127-148.

Sin, I., Stillman, S., & Fabling, R. (2020). "What Drives the Gender Wage Gap? Examining the Roles of Sorting, Productivity Differences, Bargaining and Discrimination. "*Review of Economics and Statistics*, 1-44.

Theodore, R., Taumoepeau, M., Kokaua, J., Tustin, K., Gollop, M., Taylor, N., ... & Poulton, R. (2018). Equity in New Zealand university graduate outcomes: Māori and Pacific graduates. *Higher Education Research & Development*, *37*(1), 206-221.

Yashiv, E. (2007). Labor search and matching in macroeconomics. *European Economic Review*, *51*(8), 1859-1895.

Zanin, L. (2014). On Okun's law in OECD countries: An analysis by age cohorts. *Economics Letters*, *125*(2), 243-248.

PUBLICATIONS

What Matters for Job Finding and Separation in the Long Run? Evidence from Labor Market Dynamics in New Zealand
Working Paper No. WP/2022/###