MAGKS

Joint Discussion Paper
Series in Economics

by the Universities of

Aachen · Gießen · Göttingen
Kassel · Marburg · Siegen

ISSN 1867-3678

No. 21-2020

Christopher Ball, Nicolas Groshenny, Özer Karagedikli,
Murat Özbilgin and Finn Robinson

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Coordination: Bernd Hayo • Philipps-University Marburg
School of Business and Economics • Universitätsstraße 24, D-35032 Marburg
Tel: +49-6421-2823091, Fax: +49-6421-2823088, e-mail: hayo@wiwi.uni-marburg.de

Low wage growth and job-to-job transitions: Evidence from administrative data in New Zealand*

Christopher Ball,[a] Nicolas Groshenny,[b,d] Özer Karagedikli,[c,d,e] Murat Özbilgin,[a] and Finn Robinson[a]

[a] Reserve Bank of New Zealand
[b] School of Economics, University of Adelaide
[c] South East Asian Central Banks (SEACEN) Research and Training Centre
[d] Centre for Applied Macroeconomic Analysis
[e] University of Marburg

Abstract

By using administrative data from New Zealand, we assess the relative importance of job-finding, and job-to-job transition rates for wage dynamics. We exploit the regional variation and find that wages are closely linked to job-to-job transitions and less so to the job- finding rate. Further, the impact of the job-to-job transition rate is stronger at the lower half of the wage distribution. Overall, our findings are similar to Karahan et al. (2017) for the US, which support the prominence of on-the-job search for cyclical wage dynamics.

JEL Codes: J31, J64

*The authors would like to thank Bernd Hayo, Dean Hyslop, George Kudrna, Anella Munro, Adrian Pagan, Ole Rummel, and Brian Silverstone for discussions, and seminar participants at the Reserve Bank of New Zealand, the ACE 2019 Conference in Melbourne and the NZAE 2019 Conference in Wellington for comments.
Corresponding author: Ozer Karagedikli – ozer@seacen.org.

1. Introduction

Since the global financial crisis (GFC), inflation has remained lower than central bank targets in a number of countries. Many central banks around the world have become increasingly concerned by the persistent weakness of inflation, and have been trying to understand the source of this weakness (see Jorda et al. (2019) for a recent analysis of the issue). Over this period labour markets have tightened steadily, with unemployment rates currently reaching record lows in many countries, but nominal wage growth has remained weak by historical standards.

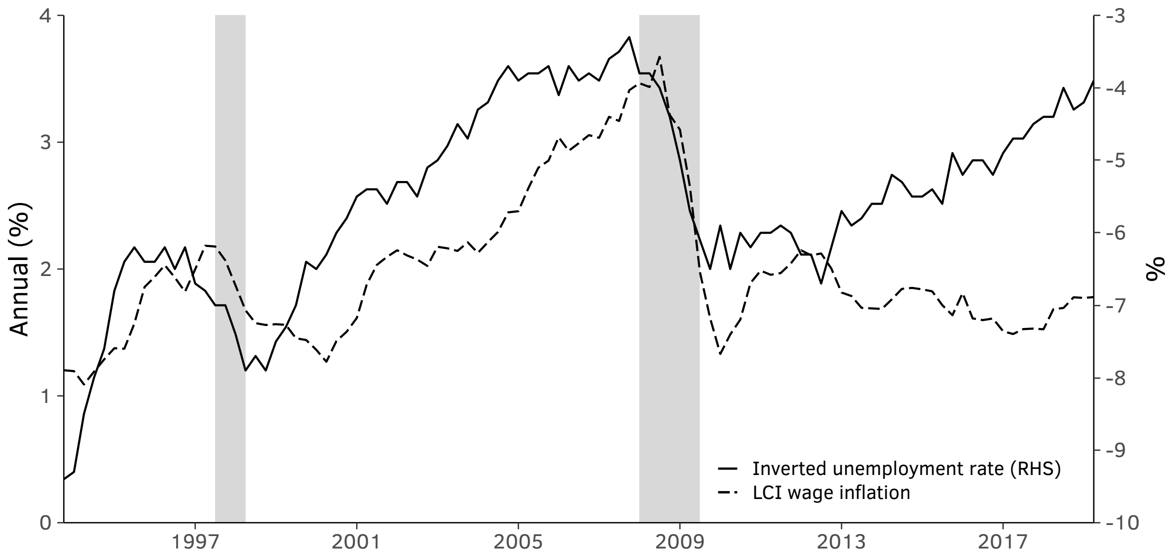
Some researchers argue that the Phillips curve, the main paradigm that the central banks use in analysing inflationary pressure, is no longer a useful framework to think about inflation dynamics (Coibion and Gorodnichenko 2015). Jorda et al. (2019) argue on the other hand that it is premature to call for the 'death' of the Phillips Curve. This issue also extends to New Zealand. Over the past few years, the Reserve Bank has been investigating possible causes of subdued inflation and low nominal wage growth alongside a declining unemployment rate and a seemingly tight labour market.[1] In New Zealand, the unemployment rate has fallen from over 6.5 percent at the end of 2009 to 3.9 percent in the June 2019 quarter. In the most recent *Monetary Policy Statement* (August 2019), the Reserve Bank noted that employment was near its maximum sustainable level. The Phillips curve relationship would suggest that when unemployment is low and there is very little slack in the labour market, then wage growth should be strong. However, Figure 1 shows that unemployment in New Zealand has declined to an 11-year low, whilst wage inflation has failed to pick up in tandem.

Search and matching models are a widely used framework for analysing wage dynamics, using rich gross labour flows data. In the canonical search and matching model of the labour market by Diamond, Mortensen, and Pissarides (henceforth DMP model),[2] wages are set through decentralized bilateral bargaining between the employer and the employee. The bargaining power of a worker is determined by the attractiveness of their outside option, namely walking away from the current match and joining the pool of unemployed workers to look for another job. Hence, the pace at which the unemployed find jobs is a crucial factor determining cyclical wage fluctuations. In the case of Nash bargaining specifically, the equilibrium wage turns out to be a weighted average of a worker's productivity and her

[1] For example, in the August 2019 *Monetary Policy Statement* low wage inflation was discussed at length.
[2] See Pissarides (2000) or Petrosky-Nadeau and Wasmer (2017) for a textbook treatment of the model.

reservation wage, where the latter is directly influenced by the job-finding rate (the share of unemployed workers who transition to employment in a given period). According to the DMP model, when the job-finding rate is high, workers have more bargaining power as they can leave the negotiating table and get a good offer elsewhere, so that, all else equal, wages increase.

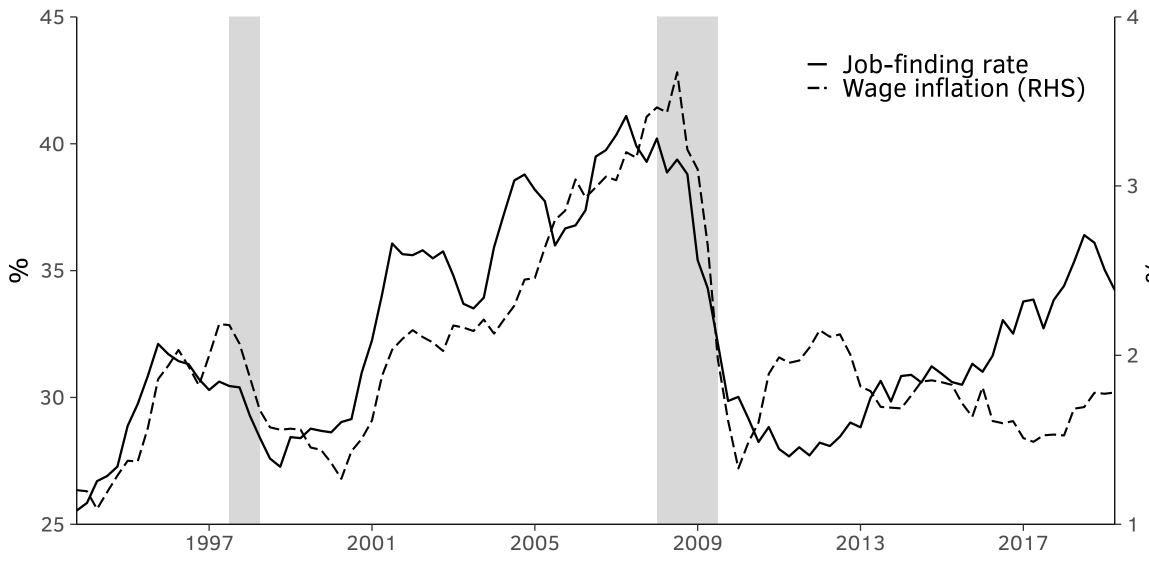
Figure 1
Wage inflation and unemployment in New Zealand



Source: Statistics New Zealand, author estimates.
Note: Grey shading indicates the start and end dates of recessions in New Zealand from the Hall and McDermott (2016). The wage measure, the LCI looks at the change in the price of a fixed quantity of work, and strips out other factors like bonuses or productivity improvements. It is therefore a close measure of the marginal cost for firms. Wage data are adjusted to exclude the impact of the Carer Wage Settlement and the larger-than-usual minimum wage increases implemented since 2017.

Figure 2 below shows the historical movements of wage growth and the job-finding rate. The two appear to co-move over most of the sample. However, since 2010 the job-finding rate has steadily increased, while wage growth has been stagnant, especially once administrative changes to wages are excluded (larger-than-usual minimum wage hikes, and the Carer Wage Settlement in 2017). The recent disconnect between wage inflation and the job-finding rate

Figure 2
Wage inflation and job-finding rate in New Zealand



Source: Statistics New Zealand, author estimates.
Note: Grey shading indicates the start and end dates of recessions in New Zealand from the Hall and McDermott (2016).Job-finding probability is a four-quarter moving average. The wage measure, the LCI looks at the change in the price of a fixed quantity of work, and strips out other factors like bonuses or productivity improvements. It is therefore a close measure of the marginal cost for firms. Wage data are adjusted to exclude the impact of the Carer Wage Settlement and the larger-than-usual minimum wage increases implemented since 2017.

suggests that the DMP model might no longer be able to explain wage dynamics in post-GFC New Zealand.

A key assumption of the DMP model is that unemployed job seekers are the only available source of labour to fill new vacancies posted by firms. This implies that an employed person has to first become unemployed before seeking another job. This simplifying assumption ignores employed people who search for jobs, a phenomenon termed on-the-job search.[3] In the United States, roughly 40 percent of all vacancies are filled by people who were employed in another job (Fallick and Fleischman 2004). Moreover, only 16 percent of the

[3]The importance of on-the-job search was highlighted by Tobin (1972) in his American Economic Association Presidential Lecture.

people who quit their jobs are next classified as unemployed while the rest move to other jobs or leave the labour force (Mukoyama et al. 2018). In New Zealand, Karagedikli (2018) showed that around 9 percent of employed people change their jobs between two quarters. The total number of job-to-job transitions is 5-6 times greater than the number of people who move from unemployment to employment within a quarter.

Moscarini and Postel-Vinay (2016, MPV) observe that a corollary of the Burdett and Mortensen (1998, BM) model of wage dispersion is that the job-to-job transition rate is the primary driver of real wages. Competition between firms for workers who are already employed (which is observed through the pace of job-to-job transitions) drives real wages higher. This prediction differs strikingly from the DMP model in which the job finding rate is the main determinant of wage fluctuations.

Motivated by this insight, MPV analyse times series data and find that the evolution of wages over the business cycle is closely linked with the pace of job-to-job transitions. Their empirical finding challenges the theoretical prediction of the DMP model that the job-finding rate should be a key determinant of wage dynamics. More specifically, in their model the primary driver of real wages is the competition among firms for employed workers.

Data limitations have partly played a role in these two competing views of wage determination from being tested. The DMP model was easy to test given the availability of long time series for the job-finding probability. However, only recently have reliable job-to-job transitions data started to emerge, mostly coming from administrative data. In a recent paper, Karahan et al. (2017) empirically test the relative explanatory power of these two views of wage setting. In contrast to the earlier attempt by MPV which used a time series of job-to-job transitions, Karahan et al. (2017) use panel data to exploit state-level variation in job-to-job transitions and job-finding rates, and measure their relative influences on wages. They find strong empirical support in favour of on-the-job search and job-to-job transitions being the prevailing sources of cyclical wage dynamics in the United States.

Our paper is closely related to Karahan et al. (2017). We use administrative data from the linked employer-employee dataset (LEED) in New Zealand regions to understand the roles of different labour flows in explaining earnings growth. We exploit the pooled cross-regional variation to understand the comparative explanatory power of the job-finding and job-to-job transition rates for wage fluctuations in New Zealand. We find that wages react strongly and significantly to the pace of job-to-job transitions and only slightly and less significantly to the job finding rate. We also find that the explanatory power of the job-to-job transition rate for wages is stronger at the lower half of the wage distribution. Overall, our findings are in line with the key results of Karahan et al. (2017) for the US, which point toward the prominence of on-the-job search for cyclical wage dynamics.[4]

Our additional contribution is to evaluate the respective explanatory power of the job-to-job transition rate and job finding rate for wage dynamics at different quantiles of the wage distribution. Our main finding that job-to-job flows dominate the job finding probability in explaining wage movements appears to be particularly noticeable at the lower deciles of the wage distribution. By calling for greater attention to be paid to the lower part of the wage distribution, our result resonates with Katz and Krueger (1999) who argue that the wage Phillips curve only holds at low wage rates. However, rather than focusing on the relationship between the unemployment rate and wages (the Phillips curve), or the relationship between the job finding rate and wages (the DMP model), our findings emphasize the relationship between job-to-job flows and wages. In addition, our data also allows us to test the effects of job-to-job transitions on the wage rates of employees who do not switch jobs, as well as the effects of separation probability.

The rest of the paper is structured as follows: Section 2 introduces the details of the administrative data used in our study. Section 3 outlines the empirical specification and estimation. Section 4 reports the main results, while section 5 provides structural vectorautoregression evidence and section concludes.

2. Data

Our data comes from a single source: the administrative Linked Employer and Employee Data (LEED) from the Inland Revenue Department (IRD).[5] LEED covers the entire population who paid some kind of Pay As You Earn (PAYE) income tax in New Zealand. From LEED, we can calculate the number of wage and salary earners who switched from one job to another job within two consecutive quarters. In addition to the job-switchers, we can also calculate the number of people who continued in the same job, and the number of people who enter into employment from unemployment (more specifically from an income support benefit,

[4]More recently, Deutscher (2019) finds similar evidence for Australia.

[5]The full data disclaimer is available on page 21.

such as unemployment benefit). In addition to the numbers, we can also calculate the wage rates (or more specifically earnings) of these people.

From LEED, we calculate the time series of earnings, job-finding rates, and job-to-job transition rates, for each of the 16 regions of New Zealand. Our data covers the 2001Q1 and 2018Q2 period, with this range being determined by the length of the time-series available from LEED. Figure 3 plots the job-to-job transition rate for each region, since 2000Q1.

Figure 3 reveals some interesting regional insights. Every New Zealand region has a mobile labour force as far as job-to-job transitions are concerned. At the same time, every single New Zealand region experienced a large decline in the job-to-job flows around the Global Financial Crisis of 2008-2009. However, not all of them recovered back to their pre-crisis levels.

3. Empirical specification and estimation

Our objective is similar to Karahan et al. (2017) where the empirical framework is not intended to establish a definitive causal relationship, rather we want to distinguish between competing theories in terms of association/relationship with wages.

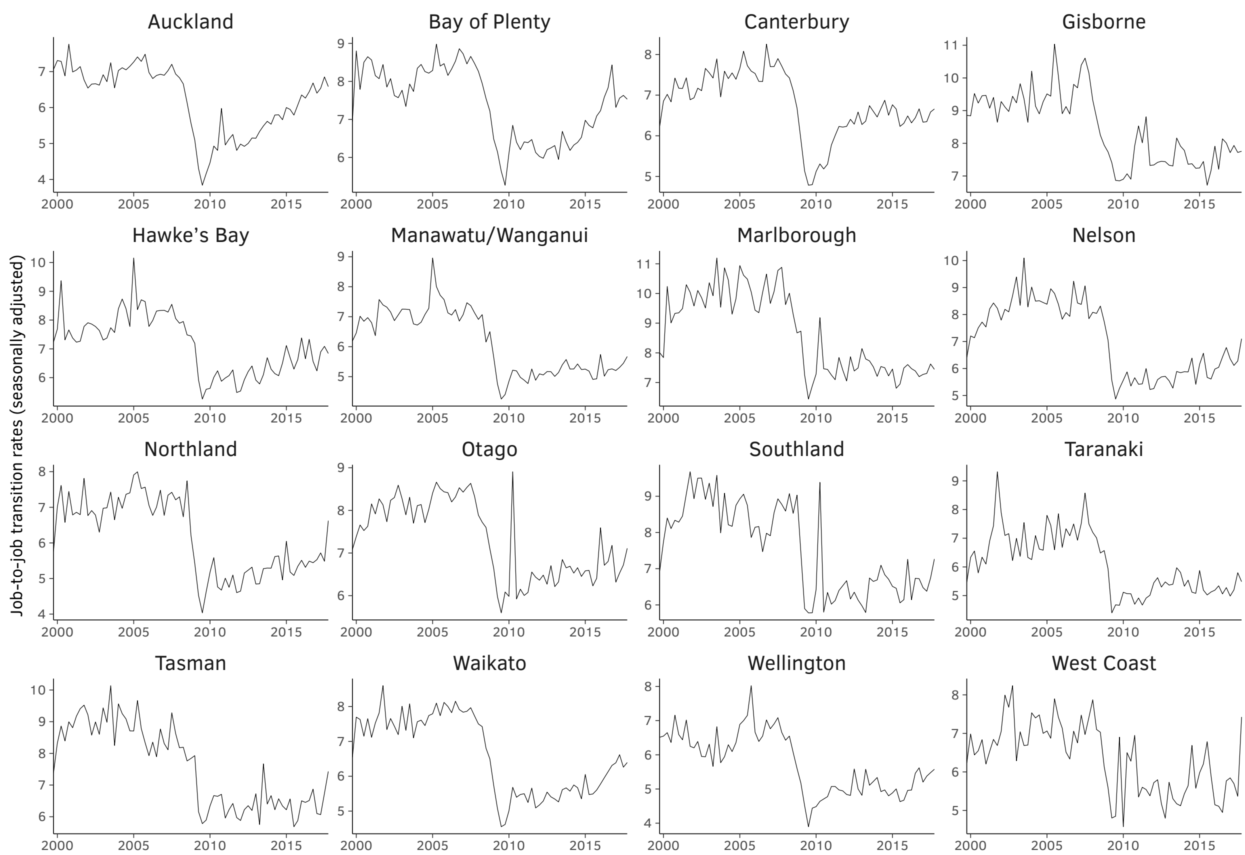
More specifically, we want to test the validity of the predictions of MPV about the relative explanatory power of job-finding and job-to-job transition rates on wage growth, but using the micro-data from New Zealand. MPV remark that, the canonical wage-posting and on-the-job search model of Burdett and Mortensen (1998) has the empirical implication that the job-finding rate of the unemployed has no predictive power on wages, whereas the job-to-job transition rate does. We follow the specification of Karahan et al. (2017), and estimate the following two fixed effects specifications:

$$\log W_{it} = \alpha_i + \alpha_t + \beta_i t + \alpha_u \Lambda^u_{it} + \epsilon_{it}, \tag{1}$$

$$\log W_{it} = \alpha_i + \alpha_t + \beta_i t + \alpha_u \Lambda^u_{it} + \boldsymbol{\alpha_e \Lambda^e_{it}} + \epsilon_{it}. \tag{2}$$

where W_{it} is the log earnings in region *i* in a calendar quarter *t*. The parameter α_i captures regional fixed effects. The term $\beta_i t$ allows for a region-specific time trend. The time fixed effect, α_t, aims to control for variation in aggregate inflation and productivity, and account for business cycle effects. We check the validity of the fixed effects by using Hausmann's

Figure 3
Regional job-to-job transition rates in New Zealand (Seasonally adjusted)



Source: Statistics New Zealand, author estimates.

specification test, and reject the null hypothesis that the region specific fixed effects are uncorrelated with the regressors. So the fixed effect estimation is appropriate.

The variable Λ^u is the quarterly transition probability from unemployment to employment, defined as total number of movements from a benefit to employment in a region during a quarter, divided by the number of benefit recipients in the previous quarter. The variable Λ^e is the regional job-to-job transition probability which captures workers that are employed by different firms in the current and the previous quarter.

To calculate Λ^e, our measure of the job-to-job transition probability, we use the share of the employed that transition from one employer to another, with no observed intervening spell of non-employment. From the administrative data, LEED, there is no unique way of creating this measure. We ensure that the person received continuous earnings throughout the quarter. Once we observe an individual receiving earnings throughout two consecutive quarters we then check if the person received income from the same employer or not. As a measurement of λ^u, we calculate Λ^u as the transition from an unemployment benefit payment (welfare) to employment in the LEED. This does have a few shortcomings in the New Zealand context. For example, not all unemployed are registered to receive an unemployment benefit. Therefore, our measure is likely to exclude the very short-term unemployed, which are probably the most likely to get a job.

Our data have some further problems, which are similar to Karahan et al. (2017): λ^e and λ^u measure the realised/observed transition probability rather than the arrival rate of job offers. The prediction of Burdett-Mortensen relates to average earnings, but this reflects in part an equal treatment constraint: all workers within a firm must be paid the same wage. More generally, it is conceivable that incumbent employees' wages are updated less frequently compared with the rate at which wage offers to new hires are adjusted, in which case, an increase in λ^e may show itself the most clearly in new hires' earnings (Karahan et al. (2017)).

4. Results

MPV point out that wages and job-to-job transitions in the Burdett-Mortensen model interact through two channels: compositional and strategic effects. The former follows from the fact that workers transit between jobs when they receive a higher wage offer. The latter follows from the competition between firms to retain workers when workers have more outside options. Both channels in the BM model favour job-to-job transitions against job-finding rates in terms of explaining the wage growth for the new hires (coming from unemployment). The strategic effect implies the same for stable earners (employees who remain in the same job) as well. In order to test these implications, we follow MPV and Karahan et al. (2017) and estimate equations 1 and 2 first for new hires, and then for stable earners. The availability of micro data enables us to distinguish between these two groups. We report these results in Table 1. The first two columns of the table present the results for the earnings of the new hires.

Table 1
Main Results

	New hires		Stable earners		All	
	(1)	(2)	(1)	(2)	(1)	(2)
Λ^u	0.5440**	0.3877*	0.1424**	0.1437**	0.3813***	0.2888**
	(0.1982)	(0.2048)	(0.0531)	(0.0526)	(0.1281)	(0.1344)
Λ^e		1.4987***		-0.0133		0.8874***
		(0.3439)		(0.1212)		(0.2254)

Number of observations: 1184.
Note: standard errors in parentheses. *** Significant at the 1 percent level.
** Significant at the 5 percent level. * Significant at the 10 percent level.

Our results for new hires are broadly in line with the results in Karahan et al. (2017). Similar to Karahan et al. (2017) and the prediction of the BM model, we find that without controlling for job-to-job transition rate, the job-finding rate is a significant predictor of earnings growth for new hires and stable earners. However, when we control for the job-to-job transition rate (column 2), the effect of the job-finding probability loses some of its explanatory power, and its coefficient is much smaller than the job-to-job transition rate, for new hires and all employees. Further, the coefficient for job-to-job transition is highly significant, and its magnitude is much higher than the job finding rate. These results support the Karahan et al. (2017) findings for new hires in the US labour markets.

More concretely, we find that a one percentage point increase in the job-to-job transition rate results in a 0.89 percent increase in earnings for all workers on average. This effect is stronger for new hires, who experience a 1.5 percent increase in earnings for a one percentage point increase in job-to-job transition probability, and insignificant for stable earners.

We also find some contrasting results in comparison to Karahan et al. (2017). They find that for new hires and stable earners, the job-finding rate becomes insignificant once adjusting for job-to-job transition rate. As seen in Table 1, we obtain different results for the stable earnings group. The job-finding rate seems to be important in explaining the wages of stable earners. The addition of the job-to-job transition rate does not seem to be effective. It is insignificant and has the wrong sign. The coefficient of the job finding rate on the other hand remains more or less the same and retains its significance.

MPV argue that the reason stable earners should benefit from increased job-to-job transitions is through rent extraction via the strategic channel. There is a possibility that job stayers could extract a wage increase from their current employer by generating an outside offer and asking the current employer to match it. Hence, the worker does not switch jobs, but get a pay rise. Our findings for stable earners indicate that the rent extraction effect may not be very strong in New Zealand.

Our results for all employees provide support for the argument that job-to-job transition rate is the primary driver of earnings growth, although not as strongly as in MPV and Karahan et al. (2017). Without taking into account job-to-job transitions, the job-finding rate seems to be highly significant. When our regressions include job-to-job transitions, on the other hand, the explanatory power of the job-finding rate diminishes, but does not vanish like the previous findings. The coefficient of the job-to-job transition probabilities is larger than that of the job-finding rate, but the implied semi-elasticity is about half of what Karahan et al. (2017) find for the US economy.

We conduct a number of robustness checks for the all employee category of our results. The first and the most obvious one is the observation from figure 2 that the job-to-job series across regions appear to have a break around 2008: The job-to-job flow figures experience a sharp fall around middle of 2008 and almost never recover to the pre-2008 levels over the subsequent decade. The Bai-Perron break test points to a break in 2008Q2, and based on this we we split the sample in two for the pre- and the post-break periods. We find that in the post 2018Q2 sample, the dominant effect of the job-to-job probability becomes more dominant while the job-finding probability still remains to be important. Overall, our result is robust towards dividing the sample into pre- and post-GFC periods (table 2).

Table 2
Pre- and post-break in 2008Q2

	Pre-2008Q2		Post-2008Q2	
	(1)	(2)	(1)	(2)
Λ^u	0.517***	0.415*	0.353***	0.276***
	(0.185)	(0.217)	(0.0919)	(0.094)
Λ^e		0.723***		1.106***
		(0.281)		(0.300)

As a complementary robustness check, we also use a dummy variable for the break period and interact it with the the slope coefficients. These results are reported in table 3. The dummy variable, $break$, which takes the value of 1 for the post-break period is included in the specification as an interaction term with job-finding probability, Λ^u and job-finding probability Λ^e. Slope interactions are not significant in any of the regressions, meaning that the coefficients on slope terms are more or less constant across two sub-samples. Overall, the break seems significant, but that comes from the intercept, but not from the slope coefficients in Λ^u or Λ^e. Therefore the results we discussed earlier remain robust.

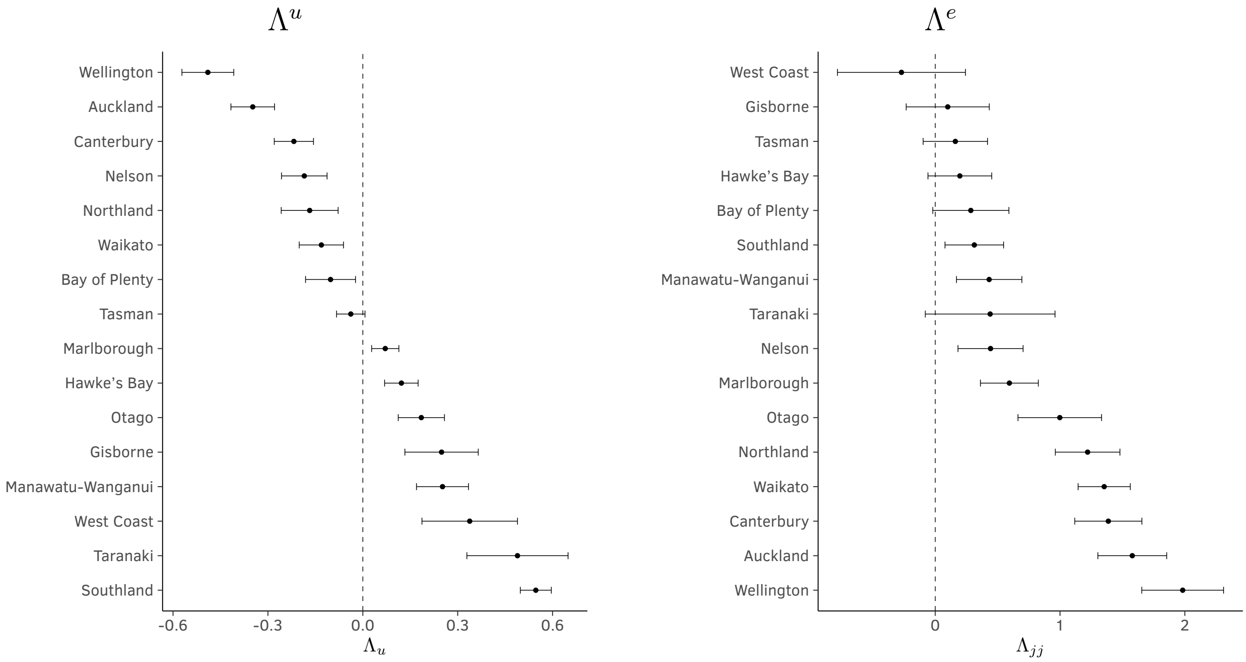
Table 3
Break test for slop coefficients

Model	Λ^u	Λ^e	break	Λ^u*break	Λ^e*break
(1)	0.427***		0.584***	-0.080	
	(0.149)		(0.149)	(0.052)	
(2)	0.316***	0.948***	0.616***	-0.041	-0.188
	(0.163)	(0.230)	(0.024)	(0.066)	(0.229)

In the specifications above, we did not include the lagged log wage in the specification. That is because the time fixed effects are expected to capture the persistent element in wages. We check this conjecture by including the lagged log wage in both specifications (1) and (2). The lagged log wage term turns out to be economically and statistically insignificant, and its inclusion does not affect noticeably the coefficients of the job finding rate and job-to-job transition rate.[6] This is perhaps largely due to the time fixed effect in the specification.

[6]These results are available upon request.

Figure 4
Λ^u and Λ^e estimates across regions



Finally, we estimate equation (3) with Seemingly Unrelated Regressions (SUR) to allow for the slope coefficients to be different across regions, and the residuals across regions to be correlated. Within this specification, we can test the equality of the slope coefficients across regions.

$$logW_{it} = \alpha_i + \alpha_t + \beta_i t + \alpha_{i,u}\Lambda^u_{it} + \alpha_{i,e}\Lambda^e_{it} + \epsilon_{it}. \tag{3}$$

We plot the region specific coefficients in figure 4. There is a significant heterogeneity across regions for both coefficients (Λ^u and Λ^e). For the former, the coefficient across regions is not as stable: with half of the parameters being negative while the other half being positive. In other words, when it comes to the breakdown across regions there does not seem to be a stable relationship between the regional job-finding probability and earnings. On the other hand, this results is driven by small, economically less significant regions. We cannot reject the equality of coefficients when we only include economically significant regions in terms of population size.

However, the relationship for the job-to-job transition rate, Λ^e is much more robust and stronger. First, 15 out of 16 regions have the sign that we expect albeit with a significant variation. Second, the relationship is stronger with larger regions with deeper labour markets such as Wellington, Auckland, Canterbury and Waikatao, which make up around 68 percent of the entire population according to 2017 figures, while all statistically significant regions make up 85 percent of the total population. When we test for the equality of the coefficients across regions we reject the null hypothesis that they have the same coefficient.

4.1 Distribution of Earnings

In this section we exploit regional variation to investigate the effects of the job-finding and job-to-job transition rates on earnings at each decile of the income distribution. We use the LEED data again to classify employed people into four categories: People who remain employed in the same job (EE), people who move into employment from unemployment (UE), people who transition from not in the labour force to employment (NE) and people who transition from one job to the next (JJ).

For each group (stayers, switchers, UE, NE) we estimate specification (2) at each decile of that particular group's earnings distribution. These results are presented in Table 2. First, similar to the Karahan et al. (2017) results we find evidence that JJ transitions have a significant effect on the earnings of people who move from not in the labour force to employment (NE). The effect of job-to-job transitions on earnings growth is significant and positive for most of the deciles of the earnings distribution of people in the NE classification. Armstrong and Karagedikli (2017) found this particular flow, NE, to be very large and active in New Zealand.[7] The job-finding rate plays almost no role on the earnings of these people. It is conceivable that given the mere size of this group there are people who move into and out of employment quickly, and they are perhaps complements to the people who transition from job to job. The effect of job-to-job transitions on the earnings of the NE flows is significantly larger than the job-finding rate.

The earnings of employees staying in their jobs (EE) is influenced by the job-finding probability, while job-to-job transitions have no effect on the earnings of this category. This could

[7] Over the 2001-2016 period, on averate 60 thousand people switched from N to E, while only 29 thousand transitions from N to U occured.

Table 4
Results Across Deciles

	EE		UE		JJ		NE	
Decile	Λ^u	Λ^e	Λ^u	Λ^e	Λ^u	Λ^e	Λ^u	Λ^e
10th	0.335***	0.235	2.597***	-0.656	0.603**	4.315***	0.297	1.553*
20th	0.205***	0.013	2.963***	-0.520	0.429**	3.377***	0.089	1.124*
30th	0.156***	-0.004	2.706***	-0.944	0.297**	2.901***	0.161	0.428*
40th	0.125***	-0.016	2.174***	-0.582	0.217	2.888***	0.092	0.672*
50th	0.124**	-0.070	1.766**	-0.286	0.177	2.919***	0.039	0.803**
60th	0.146**	-0.100	1.448**	-0.302	0.093	3.005***	-0.018	0.815**
70th	0.132**	-0.051	1.121**	-0.173	-0.014	3.077***	0.041	0.512
80th	0.120**	-0.040	0.740*	0.120	-0.076	2.882***	0.098	0.096
90th	0.125**	-0.023	0.237	0.386	-0.133	2.248***	0.025	0.712**

Note: *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

be because people who left their jobs for another job are self-selected based on having better outside options. Hence, there seems to be little empirical support for the strategic effect and the phenomenon of rent extraction by job stayers in the New Zealand context. The effect of UE transition on the earnings of EE employees (employees remaining in the same job) is, however, small economically. Nevertheless, our results suggest that the job finding rate matters for the earnings of job stayers. In this regard, our results lend support to the findings in Gertler et al. (2020).

For the earnings of the unemployed, the job-finding probability remains the key driver, while the pace of job-to-job transitions has no influence. The effect of the job-finding rate is strongest in the bottom of the earnings distribution and declines gradually. This heterogeneous effect on the income distribution is similar to the findings of Katz and Krueger (1999), where the wage Phillips curve holds most strongly for low-wage workers.

Finally, the earnings of the job-switchers (JJ category) are strongly influenced by the job-to-job transitions. Again, the effect diminishes towards the top part of the distribution. The job-finding rate also appears to have a small but significant influence on the earnings of job-switchers at the bottom of the earnings distribution (first three deciles).

5. Causal effects of job-to-job flows: Evidence from a SVAR

The previous section applied different theoretical search and matching models to the data and tested which model is linked to the wages better. As we noted earlier, the previous estimation did not claim to identify a causal relationship.

In this section, we provide a Structural Vector Auto-Regression (SVAR) model that looks at the causal effects of an exogenous movement in job-to-job flows. We estimate a four variable SVAR that includes the labour market variables consistent with the panel estimation: job-to-job transitions, not-in-labour force to employment transition, job-finding probability and wage growth. Let $y_t = (jj_t, ne_t, u_t, w_t)'$ where jj is the job-to-job transition rate, ne_t is the transition rate from not in labour force into employment, u_t is the unemployment rate, which is closely linked to the job-finding rate (ue_t) and w_t is the growth rate of nominal wage.

The structural model can be summarised by

$$B_0^{-1}B_0 y_t = B_0^{-1}B_1 y_{t-1} + ... + B_0^{-1}B_p y_{t-p} + B_0^{-1}e_t \tag{4}$$

which can then be written more compactly as:

$$B(L)y_t = e_t \tag{5}$$

The reduced form of the model is

$$A(L)y_t = u_t \tag{6}$$

By construction $u_t = B_0^{-1}e_t$. To identify the elements of B_0 and hence the structural shock u_t^{jj}, we impose a Cholesky identification, which involves a causal ordering of the variables.

$$\begin{pmatrix} u_t^{jj} \\ u_t^{ne} \\ u_t^{u} \\ u_t^{w} \end{pmatrix} = \begin{bmatrix} b_0^{11} & 0 & 0 & 0 \\ b_0^{21} & b_0^{22} & 0 & 0 \\ b_0^{31} & b_0^{32} & b_0^{33} & 0 \\ b_0^{41} & b_0^{42} & b_0^{43} & b_0^{44} \end{bmatrix} \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \\ e_{4t} \end{pmatrix} \tag{7}$$

The justification of the causal ordering in equation 7 is as follows. In New Zealand, an employed person by law is required to give their current employer at least one month's notice. Given it takes time for a person to bargain with their new employer over wage and other terms, the decision to change jobs is highly likely to have been made in the previous quarter. Because the data are sampled in the middle of each quarter, if the notice period (at least four weeks) and the bargaining combined take 6 weeks or longer, then the job-switching decisions must have been made in the previous quarter. When an employed person changes their job, the other variables in the VAR are not observed yet and are exogenous to the job-to-job transition (jj) variable. Therefore, the identification in the SVAR assumes that job transition is the most exogenous variable, and hence can be ordered above other variables. This is a reasonable timing restriction, supported by the institutional characteristics of the labour market in New Zealand.

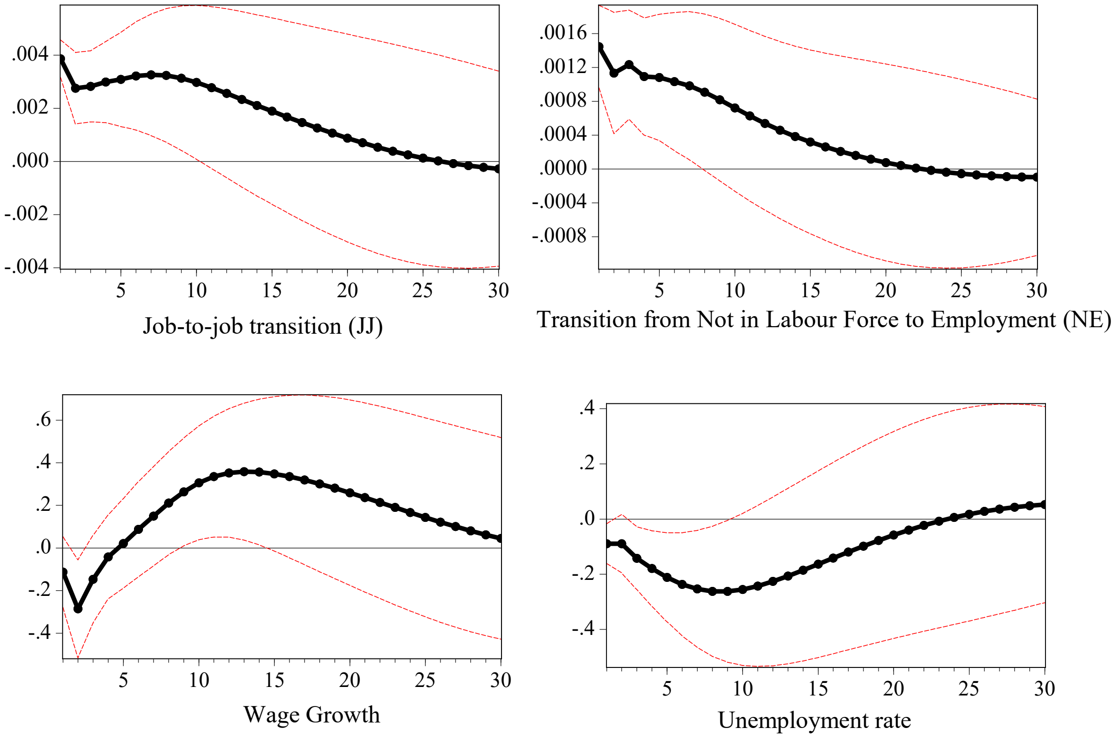
As Kilian and Lutkepohl (2018) argue, it is important to keep in mind that the Cholesky decomposition is appropriate only if the recursive structure embodied can be justified on economic grounds. They argue that [physical] constraints in the markets or institutional knowledge can be used as sources of identification restrictions. We believe that the economic argument above does justify the restriction. However, we do not take a strong position on the results of this particular SVAR, and we see these SVAR results as indicative.

We estimate the VAR(2) with OLS for the 2001Q1-2017Q4 period, where the lag length was chosen using BIC and LR both pointing to two quarters as the optimal lag-length. At the same time, the short nature of the time series does not allow us to use longer lags. We shock the system with a one standard deviation shock to the jj variable, and trace the impulse responses. Figure 5 shows the impulse response functions for the other variables.

The job-to-job transitions are highly persistent, taking around two and a half years before returning to steady-state. In response to this shock, we observe an increase in the number of people entering into the labour force (directly into employment) from the not-in-labour force. Including the people who transit from not-in-labour force into unemployment (nu) does not change the results, as they are a small proportion of the flows compared with the ne category.[8] The churn in the labour market makes it easier for the unemployed to find jobs, and consequently the unemployment rate also declines. Given the number of vacant

[8] Armstrong and Karagedikli (2017) show that in New Zealand the ne transitions are pro-cyclical, and ne flows are significantly larger than the nu transitions.

Figure 5
Impulse responses to a one standard deviation shock to Job-to-job transition rate



positions, and increasing wages, the job-finding probability and the participation margin increase. The relationship we observe is akin to the chain effects first articulated in Akerlof et al. (1988). Consistent with our panel results, we observe a persistent rise in the wage growth.

Table 5 below shows the forecast error variance decomposition that are due to the identified shock. Without making structural inferences about what this shock is, this table shows that the shocks to job-to-job transitions explain some variation in the unemployment rate, the participation margin (ne) and also wage dynamics.

Table 5
Variance decomposition due to shocks to JJ

	1	10	30
jj	100	82	82
ne	40	61	61
u	13	26	32
w	1	14	25

6. Conclusions

In this paper, we have attempted to distinguish between two models of wage determination – one where the job-finding probability plays a key role, and one where the job-to-job transition rate has a more important role. Consistent with the results in Karahan et al. (2017), our findings lend support to the importance of on-the-job search for cyclical wage dynamics.

We believe our findings can inform ongoing policy debates. Understanding the mechanism of labour market dynamics and wage fluctuations is of great significance to a central bank with a dual mandate. Macroeconomic models of the labour market typically assume that the unemployed are the only potential pool of labour competing for jobs. Modellers and policymakers have looked to the unemployment rate specifically as an indicator of pending wage pressures, with the latter presumed to then pass-through to higher prices. Recent experiences in a number of countries, including New Zealand, with low unemployment and relatively subdued wage growth has called into question whether the unemployment rate is a satisfactory summary of labour market conditions. Our findings confirm that the rate of job-to-job transitions should receive further attention. The pace of these flows is tightly associated with wage dynamics. The link between job-to-job transitions and wages may offer a more durable foundation for policy analysis.

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Integrated Data Infrastructure Disclaimer

The results in this report are not official statistics, they have been created for research purposes from the Integrated Data Infrastructure (IDI) managed by Statistics New Zealand.

Access to the anonymised data used in this study was provided by Statistics NZ in accordance with security and confidentiality provisions of the Statistics Act 1975. Only people authorised by the Statistics Act 1975 are allowed to see data about a particular person, household, business or organisation and the results in this paper have been confidentialised to protect these groups from identification.

Careful consideration has been given to the privacy, security and confidentiality issues associated with using administrative and survey data in the IDI. Further detail can be found in the Privacy impact assessment for the Integrated Data Infrastructure available from www.stats.govt.nz.

The results are based in part on tax data supplied by Inland Revenue to Statistics NZ under the Tax Administration Act 1994. This tax data must be used only for statistical purposes, and no individual information may be published or disclosed in any other form, or provided to Inland Revenue for administrative or regulatory purposes.

Any person who has had access to the unit-record data has certified that they have been shown, have read, and have understood section 81 of the Tax Administration Act 1994, which relates to secrecy. Any discussion of data limitations or weaknesses is in the context of using the IDI for statistical purposes, and is not related to the ability of these data to support Inland Revenue’s core operational requirements.