# On The dynamic of search, matching and productivity in New Zealand and Australia

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## Abstract

As far as we know there has been no, or very little, empirical examination of search models and unemployment – vacancy relationship in New Zealand. We empirically examine dynamic matching functions in the New Zealand labor market over the period 1986-2006. Further, it is well documented that although New Zealand and Australia embarked on similar wide economic reforms almost 25 years ago, the level of New Zealand's labor productivity is still lower than that of Australia (Razzak, 2007) and lower than the US productivity level (Prescott, 2002). It is has been argued that among the main explanatory variable is the low level of capital intensity – capital per hour worked - Razzak (2007) and Hall and Scobie (2005). However, there has been no formal explanation for the low level of capital intensity. This paper explains why capital investments are relatively lower in New Zealand. We do this by examining the dynamics of the labor markets in New Zealand and Australia.



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## 1. Introduction

Australia and New Zealand are interesting small and open economies the economic performances of which have been exceptional during the past 15 years. While the two countries embarked on similar wide reforms in the mid 1980s and share common features, their labor markets seem different. Table 1 decomposes GDP per person ($Y/P$), which is a common measure of income, into GDP per hour $Y/H$ (labor productivity) and hours worked per person $H/P$ (labor utilization).

The main point of table 1 is that despite the fact that New Zealanders work longer hours than the Australians, Australia is richer and more productive. Further, labor utilization $H/P$ can be decomposed into $\frac{W}{P}.\frac{LF}{W}.\frac{E}{LF}.\frac{H}{E}$, where $W$ is working age population 15 and over; $P$ is population; $LF/W$ is the labor force participation rate; $LF$ is the labor force; $E$ is employment; and $H$ is hours worked. Table 2 reports some figures.

There are two samples in table 2, 1986-1992 and 1993-2006. We report the observations for the March quarter 1986 and December 1992 and the March quarter 1993 and December quarter 2006, for both New Zealand and Australia. We report the growth rates over each sample.[i] The table gives an idea about the trend in the components of labor utilization in both countries.

The labor force participation rate grew much faster in New Zealand – twice as fast – than Australia in the second half of the sample; employment / labor ratio grew at a similar rate in both countries in the second half of the sample. Hours worked grew at a higher rate in New Zealand, but because employment in both countries increased significantly, hours / employment ratio grew at negative rates.

Razzak (2007) demonstrates that the gap in labor productivity between New Zealand and Australia is a function of the gap in capital per hour worked between the two countries and other TFP shocks. Hall and Scobie (2005) also note the capital shallowness of New Zealand as a reason for lower relative productivity.

We calculate the ratio of capital investments to hours worked as a proxy for the rate of capital intensity. Table 3 reports averages covering different samples over the period 1987 – 2007. New Zealand's capital investments per hour worked is 2/3 that of Australia, and the gap gets wider over time. This paper will give an explanation for lack of relative capital investments in New Zealand.

We will argue that one plausible reason for the relative shallowness of capital investments in New Zealand is that labor is relatively cheaper. We use the Phillips –Loretan (1991) non-linear two-sided (dynamic) least squares estimator to estimate the slop of the Merz and Yashiv's (2005) Beveridge curve recursively. This coefficients is a measure of the average quality of matching (or friction). We estimate this parameter for New Zealand and Australia.

We found that the average match quality increased in New Zealand (friction decreased) and decreased in Australia (friction increased) over the period 2000 to 2006, particularly from 2004 to 2006. Friction increases the price of labor relative to capital, hence labor is relatively cheaper in New Zealand than Australia.

De Francisco (1999) studied the unemployment-vacancy dynamic in Australia so we will not redo that. We begin with the examination of the dynamics of gross flows in the New Zealand labor market. We estimate different specifications of matching functions *a la* Diamond (1982 a, b), Mortensen (1982), Pissarides (1984, 1985) and Petrongolo, and Pissarides (2001), Mortenson and Nagypal (2007), and Stevens (2007).[ii] We find that the matching process of vacancies and workers has been costly in New Zealand, i.e., New Zealand's labor market needs to be more than twice in size in order to double hiring or matching. The parameter estimates of the matching function vary considerably over time and with the measurement of matching. There is evidence of a decline in the positive externality from workers to firms; an increase in *congestion* (negative externality from unemployed worker to another); an increase in *thick market effect* (positive externality from firms searching for workers); and although the negative externality caused by firms on each other declined over time the size is still large.

Factors that affect search intensity and the cost of searching are found to have significant explanatory power in the matching function. We tested the effect of the replacement ratio (the ratio of unemployment benefits to wages), the shares of skilled labor, females, and young workers, on the outflow from unemployment to employment.

The paper is organized in five sections. Next, a theory is presented. In sections 3 and 4 empirical results of estimating matching functions and the dynamic average quality of matching are discussed. Conclusions are in section 5. The data are described in an appendix.

## 2. Theory

The matching function approach is one particular tool to analyze friction and its effect on some labor market outcomes. Friction in the labor market stems from imperfect information and heterogeneity among other things, (1932), Diamond (1982 a, b), Mortensen (1982) and Pissarides (1984, 1985).

In a simple model of the labor market, there are two main types of players: workers searching for employment and firms posting job advertisements. Searching for, and creating jobs are costly processes. Generally, the search equilibrium is inefficient because these costs are sunk. In this model, workers and vacant jobs are considered inputs to a production technology that generates matches as output. A matching process along with an exogenous job destruction rate induce steady-state unemployment and unfilled vacancy rates. Thus, the model consists of a fixed number of unemployed workers, vacancies determined by free entry and the wages are determined by a bargaining mechanism. Matches arrive at random.

Consider a number of risk-neutral workers have the objective of maximizing the expected value of their income stream:

$$1 \quad E\sum_{t=0}^{\infty}\beta^{t}Y_{t}$$

Where ($Y_t$) is income, ($\beta$) is a discount factor, and ($E$) is the expectations operator. Workers earn wages when they are employed and nothing when they are unemployed (in a more complex model unemployed workers could earn unemployment benefits). When they are employed, workers face a probability of being separated from their jobs, ($s$). When they are unemployed workers find jobs through a matching technology:

$$2 \quad M = m(U,V)\ ,$$

where ($M$) is the number of matches, ($U$) is the number of aggregate unemployed workers and ($V$) is the number of vacant jobs in the economy. The product of unemployment and vacancies determines the number of matches. This function is increasing in both unemployment and vacancies; it exhibits a diminishing marginal productivity in each of the arguments; and possibly constant returns to scale (a testable hypothesis that will be tested in this paper).[iii] The probability that a vacancy will be matched during any period is:

$$3 \quad P^{v} = m(U,V)/V\ ,$$

And, constant returns to scale imply:

$$4 \quad M = m(U,V)/V = m((U/V),1)$$

Let $\phi \equiv V/U$ be labor market tightness (figure 1).

The probability of a vacancy being matched is:

$$5 \quad p(\phi) \equiv m(U/V,1)$$

Similarly, the probability of an unemployed worker being matched – leaving unemployment – is:

$$6 \quad \phi\, p(\phi)$$

In the steady-state the number of workers separated from their jobs (unemployed) is $s(1-U)$, and equal to the number of workers finding jobs is

$\phi\, p(\phi) U$ . In a stationary economy, the inverse of the probabilities is the mean duration of vacancies and unemployment respectively. Figure 2 plots the vacancy rates in New Zealand and Australia. Figure 3 plots the unemployment durations for New Zealand and Australia. If jobs and workers are heterogeneous then these probabilities and durations differ across the labor market. To deal with heterogeneity, the aggregate matching function should include individual characteristics when data are available.

Solving for the labor market tightness gives:

$$7 \quad U = \frac{s}{s + \phi\, p(\phi)} = \frac{s}{s + \phi\, m(U/V,1)}$$

This equation implies a downward slopping curve in the two unknowns ($U$) and ($V$). The curve shifts outward to the right as separation rate ($s$) increases, and towards the origin as matching improves. The relationship between the unemployment rate and the vacancy rate is knows as the Beveridge curve.[iv] King (2003) is a longer and very nice description of this literature.

Sketch (1) illustrates. During cyclical upturns, the labor market will be strong, with low unemployment and many vacancies (such as point a); but during a downturn, high unemployment will be matched by fewer vacancies (point b). In the short-term the labor market moves along the curve as described in the left sketch. However, over time, the slope and position of the curve can change (right sketch). There are factors that shift the curve include such as efficient job-matching; movement from outside the labor force to unemployment (assuming the same job matching); an increase (or decrease) in job churning and factors that affecting the intensity and the cost of search. For example, increased job-matching shifts the curve towards the origin (inwards). Figure 4 plots actual data of the vacancy and the unemployment rates from 1990 to 2006. The plot unambiguously shows that the curve has shifted towards the origin over time and the slope has changed**.** Figure 5 plots the Australian Beveridge curve, where shifts toward the origin are less obvious.

In this model, the number of workers is fixed. Thus, the value of ($\phi$) is determined by the vacancy. Each period, a vacancy incurs a cost if it is unfilled. The cost is given by a constant ($C$). The vacancy also produces output when it is filled, ($Y$). Firms keep posting vacancies until the marginal cost is equal to the marginal benefits. Wages are determined by the Nash bargaining, where the parameter ($\gamma$) is the workers' bargaining power. Thus:

$$8 \quad Y = \frac{1 - \beta + \beta\,(s + \gamma\, \phi\, p(\phi))}{\beta(1-\gamma)\, p(\phi)}\; C$$

Solving equations (7) and (8) yields the steady state values of both unemployment and vacancies. In equilibrium, unemployment is decreasing in output; increasing in the cost of vacancy, the separation, and the workers' bargaining power.

In New Zealand, output has been growing (the average annual GDP growth rate is 2.4 percent over the period 1992 – 2006); the bargaining power of workers has declined with the declining power of the unions, figure 6. Note that the level of unionization is much higher in Australia, which might have some implications for the cross-Tasman movement of trade workers. The job separation figures have been falling for males and constant for females, figure 7. Short-term duration of unemployment (less than 4 weeks) has been volatile and trending upward, figure 8, but long-term duration of unemployment (over 52 weeks) has been falling, figure 9. Workers stay unemployed for longer time in Australia. Both short and long term unemployment durations are larger than those of New Zealand's.

## 3. Matching process

This section documents estimates of the matching functions for New Zealand. Matching functions summarize trading technologies between firms that post job vacancies (in newspapers, magazines, on the net, employment agencies, etc) and workers who look for jobs (the unemployed). Matching is a complex process. The matching function, however, is a simple representation of this process, which gives the number of jobs formed at any moment in time in terms of the number of workers looking for jobs and the number of firms looking for workers. A typical matching function is given by the Cobb-Douglas function:

$$9 \quad M_t = U_t^{\alpha_1} V_t^{\alpha_2} e^{\varepsilon}$$

The parameter $\alpha_1$ measures the positive externality from workers to firms and $\alpha_2$ measures the positive externality caused by firms on searching workers (thick-market effect); thus $\alpha_1 - 1$ is a measure of the negative externality or congestion caused by one unemployed worker on others; similarly $\alpha_2 - 1$ measures the negative externality from one firm to another. The magnitudes of $\alpha_1$ and $\alpha_2$ are sensitive to the measurement of the dependent variable $M_t$, the sample size among other things.[v]

We will estimate the matching function for New Zealand only because the Australian gross flows data are only available from 1997. We use two common measures for the dependent variable $M_t$: (1) total outflows from unemployment, which includes outflows from unemployment to unemployment and from unemployment to 'not' in the labor force; (2) outflows from unemployment to employment only. New Zealand has no vacancy data. However, we have a reasonably consistent and long time series of job ads. The data have been produced by the ANZ bank (a commercial bank) since the 1990s. The data include job ads in newspapers in the three big cities, Auckland, Wellington and Christchurch, which they cover most of the labor market in New Zealand. Recently, they added job ads from other smaller cities and also ads posted on Net. For consistency, we will use the big three cities as a proxy for the New Zealand labor market and will ignore ads posted on the Net to avoid potential double counting.

We seasonally adjusted the data using a variety of models and picked the models that best fit using a variety of commonly used information criteria. Figures 10 to 13 Plot the data used in estimating the matching functions. The outflows data have a hump in the early 1990s. For years following the reform in 1984, unemployment continued to rise sharply, possibly, for two reasons. First, it increased because of the disinflation process and the change in expectations about prices and consequently real wages. Second, unemployment increased because of the privatizations of state-owned enterprises, where more workers were laid off. Once the effects of the reform were understood and inflation expectations were brought down, unemployment continued to fall with the exception of the Asian crises period in 1997-1998, which caused a small recession in New Zealand. Employment growth kept increasing since the 1990s.

Job ads experienced a couple of dips one is large in the early 1990s at the same time of the increase in unemployment then another smaller one during the Asian crises. The Australian vacancy data look almost the same as New Zealand's up to 1998 then there is a huge increase in vacancies.

The trend is examined by testing for unit root. A variety of commonly used unit root tests do not reject the hypothesis of unit root, which might be a sign of low power of the tests. We are cautious that the tests are picking up the effect of changes in policy from the mid 1980s up to1992. New Zealand's reform process started in 1984 and continued until 1992. Whether the data have unit roots (and cointegrtaed) or do not have unit roots (stationary), OLS estimates for regressions in levels will be super-consistent. However, the sharp increase (the hump) in outflows and the dip in job-ads in the early 1990s hampers the estimation considerably. A more appropriate sample would be from 1994Q1 to 2006Q2 instead. There is another problem, the unemployment and job ads might not be strictly exogenous. If they are not then OLS estimates will be biased and inconsistent.[vi]

Petrongolo and Pissarides (2001) report about 20 to 22 international estimates of $\alpha_1$ and $\alpha_2$ using an equation like (9) with different methods, different dependent variables etc. The average of these international estimates for $\alpha_1$ is 0.49 and 0.50 for $\alpha_2$. They sum to one, hence most of the international matching functions exhibit constant returns to scale. These estimates are different in the case of New Zealand. We estimate the coefficients using both non-linear least squares and linear least squares methods. Table 4 reports the results of the estimates of the nonlinear function and table 5 reports those of the linear model.

The first column in table 4 reports the coefficients and some statistics. The table reports two sets of results. The first is when matching $M_t$ is measured by total outflows, where four sets of results are reported. There are two samples: a sample from 1990Q1 to 2006Q2 and another from 1994Q1 to 2006Q2, which covers the period following the hump shown in figure 10. The other set of results corresponds to the case where $M_t$ is proxied by outflows from unemployment to employment only. This is also estimated for two different samples.

The coefficients $\alpha_1$ and $\alpha_2$ vary in magnitudes. The coefficient $\alpha_1$, which corresponds to unemployment, measures the positive externality from workers to firms. The coefficient $\alpha_2$ measures the positive externality caused by firms on the searching workers (i.e., thick market effect). So $\alpha_1 - 1$ is a small negative externality (congestion) inflicted by an unemployed worker on another. Similarly, $\alpha_2 - 1$ measures the negative externality by firms on each other.

Over the period 1990 to 2006, $\alpha_1$ is large, near unity when the dependent variable is total outflows. The coefficient estimate becomes smaller (0.8) over the sample 1994-2006. This suggests that positive externality from workers to firms seems to have declined over time. The magnitudes of the coefficient estimates change significantly when we use the outflows from unemployment to employment as a dependent variable. In the sample from 1990 to 2006, the coefficient estimate $\alpha_1$ is 0.6, much smaller that the earlier estimates. It becomes 0.3 in the sample from 1994 to 2006. These estimates also suggest a decrease in positive externality from workers to firms. The results suggest that $\alpha_1 - 1$ increases over time indicating an increase in the congestion effect caused by the unemployed on other unemployed workers.

However, $\alpha_2$ is small and negative in the first two regressions and positive but small after 1994. Negative values probably imply a misspecification. In the regressions where the dependent variable is the outflows from unemployment to employment the estimated coefficient $\alpha_2$ becomes positive and much larger over the period from 1994-2006, which suggests an increase in the positive externality caused by firms on searching workers (thick market effect). However, there is still a significant negative externality from one firm to another. These results are consistent with the increase in skill shortages with unemployed workers of very different skills.

Although the coefficient of unemployment $\alpha_1$ is closer to 0.50 than that of job-ads in some of the regressions, the hypothesis that the coefficients $\alpha_1 + \alpha_2 = 1$ is rejected. The matching function in New Zealand does not exhibit constant returns to scale but rather decreasing returns to scale. Decreasing returns to scale mean that the New Zealand labor market needs to be more than double in size in order to double matching. The matching process in New Zealand has been costly. Imposing a constant return to scale on the matching function and testing it indicates that the coefficient is significantly different from unity, i.e., it does not hold.

We also estimate the coefficients $\alpha_1$ and $\alpha_2$ recursively over the sample Dec 2000 to June 2006 (the model includes time trend). We estimate the model up to September 2000 then we add one observation and re-estimate and so on so forth. In figure 14 we plot the recursive coefficient estimates from model (1) in table 4, where the dependent variable is total outflows and from model (2), where the dependent variable is outflows from unemployment to employment. Both estimates declined over time, which confirms our earlier interpretation that positive externality from workers to firms has been declining (downward drift) and that the function has shifted over time. Conversely and without plotting, $\alpha_1 - 1$ and $\alpha_2 - 1$ must have increased over time, which indicate an increase in the positive externality caused by firms on searching workers.

The term trend squared has a negative and a significant coefficient, which also suggests that the matching function shifted downwards. The regression's residuals are not white noise, which means there are some dynamic that need to be explained.

The fit of the model deteriorates as the sample gets shorter, i.e., the value of adjusted $R^2$ declines with the sample size. The $DW$ statistics become very small when the dependent is the outflows from unemployment to employment.[vii] We tested the residuals for Whiteness using the cumulated periodogram test Maximum gap. It has a value > than the critical values at the 1, 5 and 0 percent levels. The residuals are, therefore, not white noise, which means that there is some unexplained dynamic that we have to explain.

## 3.1 More on estimation

To deal with unexplained dynamics in the outflows from unemployment to employment and possible misspecification, we estimate a linear function (not in log), Pissarides (1986).

$$y_t = (aL)y_t + (1 + b_1 L + b_2 L^2 \cdots b_i L^i)(V/Y)_t + c_1 v_t + c_2 u_t + c_3 \Delta v_t + c_4 \Delta u_t + c_5 I_t + c_7 \widetilde{M}_t + \psi_t \tag{10}$$

The idea behind equation (10) is that in the steady-state, the rate of outflows from unemployment to employment (the outflow from unemployment to employment / the number of unemployed workers) $y_t$ depend on the vacancy rate $v_t$, the unemployment rate $u_t$, variables that affect search intensity $I_t$, and variables that proxy structural mismatches in the economy $\widetilde{M}_t$.

There are many variables that could be used to measure search intensity, but data are readily available for three. These three variables are (1) the share of young workers age 15-19 in working age population. Younger workers might have lower search intensity; (2) the share of females in working age population, where more female involved in search the higher the flow from unemployment to employment; and (3) the replacement ratio, which is the ratio of total unemployment benefits to wages, which increases the cost of search. For mismatch ($\tilde{M}_t$), the share of workers with university and post university qualifications (skilled labor) to total employed workers is used. Results are reported in table 5.[viii] There are three sets of results. The first two are in columns 2-5 and the third is in columns 6 and 7.

*The first set of results*: There is a statistically significant lagged dependent variable, thus outflows are persistent. The contemporaneous ratio of vacancy to unemployment is statistically significant and has a positive sign. The sum of the four lagged values is small and negative. The vacancy rate is negative and significant while the unemployment rate has no effect on the outflows. The latter result is quite the opposite of what we had in the non-linear matching function that we estimated earlier. These results are not unique to New Zealand. Pissarides (1986) found similar results for Britain. The changes in vacancy and in unemployment rates are negative and significant, same as in Pissarides (1986). These results indicate decreasing returns to scale. The trend and squared trend are insignificant.

*The second set of results*: we replaced the trend in equation (10) with three shift variables: for mismatching we added the share of university and post-university qualified workers in total employment; and for search intensity we added the share of female workers in working age population and the share of workers aged 15 to 19 in working age population. Most of the previous results still hold. The share of skilled workers seems significant and negative. It indicates that the level of skills has been reducing the matching. This might mean that the vacancies created in the economy are mostly for unskilled labor. Neither female nor the young workers share in working age population is significant.

*The third set of results*: We change the sample to March 1994 – June 2006 because the replacement ratio (the ratio of total unemployment benefits to wages) is only available from 1994. Most of the previous results still hold. The replacement ratio is insignificant.

Figure 15 plots the actual and fitted values of these three regressions. The Cumulated Periodogram test indicates that the residuals are serially uncorrelated. However, if these variables are cointegrated we have to use a more suitable estimator than OLS. A proper estimation method is the Phillips-Loretan (1991) non-linear two-sided dynamic least squares.[ix]

$$y_t = \alpha\, x_t + \sum_{i=-k}^{k} \gamma_i \Delta x_{t-i} + \rho(y_{t-1} - \alpha\, x_{t-1}) + \varepsilon_t \tag{11}$$

where $x_t$ is a vector that includes the vacancy rate, the unemployment rate, the ratio of vacancy to unemployment, variables that proxy $I_t$ and $\tilde{M}_t$. Equation (11) is estimated over the period 1995Q1-2004Q2 because some data are not available for earlier and latter periods and because of the lag and lead differences. The results are reported in table 6. The long-run function $x'_{t-1}\alpha$ represents the long-run. We plot it against the actual value of outflows from unemployment to employment in figure 16. Clearly, there is a good correlation between matching and the levels of the explanatory variables in the long run.

These results are different from those reported earlier. All the level variables are significant. The signs remained unchanged. The dynamic effects are more interesting. All the contemporaneous changes are significant, except the share of young workers, which is insignificant and the replacement ratio, which is only borderline significant.

The positive signs in the contemporaneous, lag and lead changes of the share of skilled workers are most interesting. Remember that the level has a negative sign. The interpretation of the positive signs of the differenced variables is that the firm's expectation of an increase in the level of skills next period induces more investments in skill-complementary technology. The firms posts vacancies for skilled labor, hence the increase in matching.

For the share of females, all the changes – contemporaneous, lag and lead – are positive and significant. The increase in female participations clearly improved the matching. A one percent increase in female participation leads to 0.30 percent increase in matching; a one percent increase in last period change in female participation increases matching by 0.35 percent; and a one percent increase in expected next period change in female participation increases matching by 0.32 percent.

The contemporaneous and lagged values the share of young workers and the replacement ratio seem to have insignificant impact on matching. However, a one percent increase in the expected share of young workers in working age population increases matching by 0.15 percent. And, a one percent increase in the expected replacement ratio ($\Delta_{t+1}$) leads to a ½ percent decrease in matching.

## 4. Friction and the quality of matching

Razzak (2007) explains the gap in labor productivity between New Zealand and Australia by capital intensity and a few TFP shocks. Capital intensity, however, is a major culprit. If New Zealand's annual capital intensity growth increase by 1 percent relative to Australia, labor productivity growth can increase by as much as a ¼ percent. Hall and Scobie (2005) also noticed the same problem of 'shallow capital' in New Zealand. The question is why New Zealand has a lower capital intensity level than Australia? The answer might be found in the labor market because the dynamic (and policies) of the labor market affects the relative price of labor to capital.

We use the Phillips – Loretan (1991) two-sided dynamic least squares estimator below to estimate the job destruction rate and the average match quality (friction) from December 1990 to December 2000 for both New Zealand and Australia. We then recursively estimate the function, observation by observation from March 2001 to March 2006. This gives us 22 estimates of $\psi$ and $q$ over time.

12 $$n_t = qv_t + \sum_{i=-k}^{k} \gamma_i \Delta v_{t-i} + \rho(n_{t-1} - qv_{t-1}) + \upsilon_t$$

Where $n_t$ is the log of the employment rate, $v_t$ is the log vacancy rate and $\rho$ is $1-\psi$. The regression includes a constant term, trend and trend squared terms.

We only plot the estimated $q_t$ for the period March 2004 to March 2006 in figure 17. This covers the period when the labor market tightness in Australia relative to that in New Zealand, increased significantly. In figure 17, Visually, there is a positive drift in the estimates for New Zealand. The higher the value of $q_t$ the higher the matching quality and the lesser is the friction in the labor market, which implies that the increase in employment is higher for a given number of vacancies making investments in labor relatively cheaper than capital. Less friction implies lower relative price of labor.

The average estimated value of $\psi$ over the period March 2001 to Mar 2006 (the average rate of job destruction) is about 20 percent. The rate of job destruction is almost constant over time, but seems to vary with the business cycle. It increases to 22 percent in 1997-1998 Asian crises. This estimate is slightly larger than the estimates reported in Carrol *et al.* (2002) who used micro data, different samples, and different methodology.[x]

For Australia, using data from the Australian Bureau of Statistics and the same method of estimation, average $q$ declines over time, i.e., increase in labor market frictions. This seems more consistent with tight labor markets with low unemployment rates.

Comparing New Zealand and Australia's results suggest that the Australian firms seem to face stronger friction in the labor market, which makes investing in capital rather a cheaper option for them. Also, the average rate of job destruction is 8 percent, which is several times lower then that of New Zealand. The results for Australia seem consistent with some theoretical models, Basu (2006).

These estimates, for New Zealand and Australia seem consistent with the stylized facts that Australia's labor productivity is relatively higher than New Zealand's. For New Zealand, the higher value of the estimate of the average quality of matching (lesser is the friction in the labor market) implies that the increase in employment is higher for a given number of vacancies making investments in labor relatively cheaper than capital.

For Australia, the lower value of the estimate of the average quality of matching (higher is the friction in the labor market) implies that the increase in employment is lower for a given number of vacancies making investments in labor relatively more expensive than capital.

Contrary to New Zealand, Australia's labor has more capital to work with, thus higher labor productivity. And, New Zealand firms post more low-skill vacancies and match them with relatively low-skill workers than Australia because New Zealand firms have low capital intensity, thus do not have the incentive to create high-skilled jobs.

## 5. Conclusions

The dynamics of the gross outflows have been examined via matching functions, and some interesting and meaningful description of the labor market has been drawn. However, the focal point of this paper was to explore whether there is a meaning explanation of the relatively low labor productivity in New Zealand in the process of search and matching (friction). The main conclusion is that New Zealand labor market arrangements seem to have lowered the price of labor relative to capital, which induced firms to invest more in labor than capital. The opposite is true in Australia. More capital makes existing labor more productive.

To summarize, we estimates a Cobb-Douglas matching function in different specifications. We found decreasing returns to scale, which means that to double the matching of vacancies and unemployed workers the New Zealand labor market must be more than twice as big. The matching function seems to have shifted overtime. The estimation also reveals some unexplained dynamics most likely resulting from misspecification. We found that positive externality from unemployed workers to firms declined over time; congestion – the negative externality from unemployed worker to another – has increased over time; positive externality from firms to workers – thick worker effect – increased over time; and negative externality from one to another has declined.

To remedy the unexplained dynamic problem, we estimated a linear matching function using an appropriate dynamic estimation method and augmented it with variables to measure the search intensity and the cost of search, such as the share of females in working age population, the share of young workers in working age population, the share of skilled labor in total employment, and the replacement ratio. We found evidence of their significance in affecting matching.

New Zealand's productivity is low relative to Australia. It is well documented that New Zealand has a low capital intensity relative to Australia and that this 'capital shallowness' explain lots of the labor productivity gap between the two countries. The question this paper asks is why New Zealand has relatively low capital intensity and whether the answer lies in the labor market?

Our recursive estimates of the average quality of matching (friction) increased (declined) more in New Zealand than Australia over the past 6 years. For New Zealand, the higher value of the estimate of the average quality of matching (lesser is the friction in the labor market) implies that the increase in employment is higher for a given number of vacancies making investments in labor relatively cheaper than capital.

For Australia, the lower value of the estimate of the average quality of matching (higher is the friction in the labor market) implies that the increase in employment is lower for a given number of vacancies making investments in labor relatively more expensive than capital.

Contrary to New Zealand, Australia's labor has more capital to work with, thus higher labor productivity. And, New Zealand firms post more low-skill vacancies and match them with relatively low-skill workers than Australia because New Zealand firms have low capital intensity, thus do not have the incentive to create high-skilled jobs.

The micro level evidence seems also somewhat consistent with the results above. Hyslop and Mare (2006) study the compositional changes of workers and firms in New Zealand. They found that the average worker unobserved fixed effect on earnings has declined by 5 percent over the period 1999-2005. Their interpretation was that during upward phase of the business cycle (expansionary employment) more low-productivity workers get drawn into the labor market.

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Table 1: GDP per Working Age Population (Australia=100)

| | GDP per Person | GDP per Hour | Hour per Person |
|---|---|---|---|
| 1987Q2-1992Q4 | 74.1 | 72 | 103 |
| 1993Q1-2006Q4 | 71.5 | 66 | 108.4 |

Table 2: Decomposition of Labor Utilization

| **New Zealand** | $W/P$ | LF Participation Rate | $E/LF$ | $H/E$ |
|---|---|---|---|---|
| March 1986 | 0.77 | 67.1 | 0.96 | 34.9 |
| December 1992 | 0.81 | 63.5 | 0.90 | 34.2 |
| **Growth Rate** | **5.0%** | **-5.51%** | **-6.4%** | **-2.0%** |
| March 1993 | 0.82 | 63.3 | 0.90 | 35.7 |
| December 2006 | 0.83 | 68.0 | 0.96 | 34.4 |
| **Growth Rate** | **1.2%** | **7.16%** | **6.4%** | **-3.70** |
| | | | | |
| **Australia** | | | | |
| March 1986 | 0.76 | 61.57 | 0.92 | 29.78 |
| December 1992 | 0.77 | 62.61 | 0.89 | 28.15 |
| **Growth Rate** | **1.3%** | **1.67%** | **-3.15%** | **-5.6%** |
| March 1993 | 0.77 | 62.47 | 0.89 | 30.41 |
| December 2006 | 0.79 | 64.72 | 0.95 | 29.32 |
| **Growth Rate** | **2.5%** | **3.5%** | **6.5%** | **-3.6%** |

Table 3: Capital investments per hour-worked (Australia = 100)

| | Average |
|---|---|
| 1987Q-1992Q4 | 66.53 |
| 1993Q1-2007Q1 | 66.91 |
| 2003Q1-2007Q1 | 64.10 |

Table 4: Estimates of the Matching Function 1990Q1 – 2006Q2
$M_t = U_t^{\alpha_1} V_t^{\alpha_2} e^{\varepsilon}$; U in the number of unemployed. V is job ads.

| | $M_t$: total outflows [i] | | | | $M_t$: outflows from unemployment to employment [ii] | | | |
|---|---|---|---|---|---|---|---|---|
| Sample | 90q1-06q2 | 90q1-06q2 | 94q1-06q2 | 94q1-06q2 | 90q1-06q2 | 90q1-06q2 | 94q1-06q2 | 94q1-06q2 |
| $\alpha_1$ | 0.96 (0.0000) | 0.95 (0.0000) | 0.81 (0.0000) | 0.80 (0.0000) | 0.60 (0.0000) | 0.60 (0.0000) | 0.30 (0.0000) | 0.37 (0.0000) |
| $\alpha_2$ | -0.06 (0.0251) | -0.06 (0.0194) | 0.12 (0.0760) | 0.12 (0.0693) | 0.06 (0.0257) | 0.07 (0.0363) | 0.32 (0.0000) | 0.32 (0.0000) |
| Trend*1000 | -0.085 (0.9079) | - | -1.85 (0.0636) | - | 1.57 (0.0109) | - | -0.35 (0.6628) | - |
| Trend Sq.*1000 | - | -0.0015 (0.8407) | - | -0.016 (0.0682) | - | 0.016 (0.0264) | - | -0.0024 (0.7403) |
| $\overline{R}^2$ | 0.90 | 0.90 | 0.83 | 0.83 | 0.59 | 0.59 | 0.45 | 0.45 |
| $DW$ [iii] | 1.64 | 1.64 | 1.66 | 1.65 | 0.70 | 0.71 | 0.85 | 0.85 |
| $SE$ [iv] | 6.34 | 6.34 | 5.34 | 5.35 | 1.87 | 1.86 | 1.56 | 1.56 |
| Max. gap | 0.1397 [v] | 0.1397 [v] | 0.1498 [vi] | 0.1517 [vi] | 0.4960 | 0.4957 | 0.4151 | 0.4151 |
| $\chi_1^2$ [vii] | 0.0000 | 0.0000 | 0.0008 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

-i These are total outflows from unemployment to unemployment, not in labor force, and to employment.
-ii These are outflows from unemployment to employment only.
-iii The DW statistic requires a constant term in the regression, nevertheless, it is a useful statistic.
-iv The Newey-West procedure is used to compute the variance-covariance matrix.
-v This is the Cumulated Periodogram test, which tests the gap from the density function of a white noise process. The Approximate rejection limits are 1%=0.2037, 5%= 0.1700 and 10%= 0.1525. The null hypothesis is white nose.
-vi The Approximate rejection limits are 1%=0.2881, 5%= 0.2404 and 10%= 0.2157.
-vii this is the P value of the $\chi_1^2$ test for the restriction $\alpha_1 + \alpha_2$=1.
P vales are in parentheses.

Table 5: The Linear Matching Functions OLS Estimates

10 $y_t = (aL)y_t + (1 + b_1 L + b_2 L^2 \cdots b_i L^i)(V/Y)_t + c_1 v_t + c_2 u_t + c_3 \Delta v_t + c_4 \Delta u_t + c_5 I_t + c_7 \tilde{M}_t + \psi_t$

| | March 1990- June 2006 | | | | March 1994-December 2004 | |
|---|---|---|---|---|---|---|
| Variable | Coefficient | P value | Coefficient | P value | Coefficient | P value |
| Constant | 0.15 | 0.1699 | 0.88 | 0.5427 | -3.16 | 0.1203 |
| $y_{t-1}$ [i] | 0.59 | 0.0000 | 0.54 | 0.0000 | 0.41 | 0.0060 |
| $(V/U)_t$ [ii] | 0.0027 | 0.0000 | 0.002 | 0.0002 | 0.004 | 0.0000 |
| $(V/U)_{t-1}$ | -0.002 | 0.0038 | -0.001 | 0.0236 | -0.003 | 0.0037 |
| $(V/U)_{t-2}$ | 0.0004 | 0.3510 | 0.0005 | 0.2730 | 0.000 | 0.9413 |
| $(V/U)_{t-3}$ | -0.0011 | 0.0129 | -0.0011 | 0.0140 | -0.001 | 0.0274 |
| $(V/U)_{t-4}$ | 0.0007 | 0.0386 | 0.0007 | 0.0597 | 0.001 | 0.0076 |
| $v_t$ | -0.024 | 0.0504 | -0.027 | 0.0449 | -0.02 | 0.2635 |
| $u_t$ | 0.007 | 0.3732 | -0.01 | 0.3624 | -0.008 | 0.3680 |
| $\Delta v_t$ | -0.021 | 0.0898 | -0.01 | 0.0296 | -0.04 | 0.0439 |
| $\Delta u_t$ | -0.017 | 0.0547 | -0.018 | 0.0203 | 0.003 | 0.7616 |
| $Trend * 1000$ | 0.0015 | 0.2358 | - | - | - | |
| $Trend^2 * 1000$ | -0.00002 | 0.1537 | - | - | - | |
| $\tilde{M}_t$ : | | | | | | |
| Skills [iii] | - | | -0.007 | 0.0743 | -0.005 | 0.3887 |
| $I_t$ : | | | | | | |
| Female [iv] | - | | -0.009 | 0.7162 | 0.06 | 0.0839 |
| Young [v] | - | | -0.005 | 0.3087 | 0.009 | 0.3024 |
| Replacement Ratio [vi] | - | | - | - | 0.05 | 0.7444 |
| $\bar{R}^2$ | 0.91 | | 0.91 | | 0.90 | |
| *Max Gap* [vii] | 0.0775 | | 0.0915 | | 0.1437 | |

i- The dependent variable is the rate of outflows from unemployment to employment.
ii- V is the ANZ ads in the three big cities Auckland, Wellington and Christchurch and U is the HLFS number of unemployed workers. Small letters denote the rates.
iii- Skills is the share of employed workers with university and post university qualifications in total employment.
iv- Female is the share of female workers in working age population.
v- Young is the share of workers age 15-19 & 20-24 in working age population.
vi- Replacement ratio is total unemployment benefits to wage of all employed workers fulltime and part-time ratio.
vii- Residuals were diagnosed using a number of tests for whiteness. Among these tests is the Cumulated Periodogram test, which tests the gap from the density function of a white noise process. The Approximate rejection limits are 1%=0.2881, 5%= 0.2404 and 10%= 0.2157. The null hypothesis is white nose.

Table 6: The Phillips – Loretan Dynamic two-sided least squared [i]

11 $y_t = \alpha x_t + \sum_{i=-k}^{k} \gamma_i \Delta x_{t-i} + \rho(y_{t-1} - \alpha x_{t-1}) + \varepsilon_t$, where $x_t$ includes: vacancy rate, unemployment rate, the ratio of vacancy to unemployment, the share of skilled labor in employment, the share of females in population, the share young workers in population and the replacement ratio. Sample 1995Q1 – 2004Q2.

| Variable | Coefficient | $t$ statistic | P value |
|---|---|---|---|
| $v_t$ [ii] | -0.15 | -2.35 | 0.0184 |
| $u_t$ | 0.11 | 2.88 | 0.0038 |
| $(V/U)_t$ | 0.01 | 2.71 | 0.0066 |
| $Skills_t$ [iii] | -0.06 | -4.97 | 0.0000 |
| $Female_t$ [iv] | 0.03 | 2.82 | 0.0047 |
| $Young_t$ [v] | -0.04 | -2.26 | 0.0235 |
| $\mathrm{Re}\,place_t$ [vi] | -1.27 | -2.20 | 0.0272 |
| $\Delta v_t$ | 0.13 | 2.75 | 0.0058 |
| $\Delta v_{t-1}$ | -0.003 | -0.10 | 0.9129 |
| $\Delta v_{t+1}$ | 0.03 | 1.35 | 0.1739 |
| $\Delta u_t$ | -0.11 | -3.70 | 0.0002 |
| $\Delta u_{t-1}$ | 0.02 | 1.51 | 0.1305 |
| $\Delta u_{t+1}$ | -0.02 | -1.23 | 0.2172 |
| $\Delta(V/U)_t$ | -0.007 | -2.95 | 0.0032 |
| $\Delta(V/U)_{t-1}$ | 0.000 | 0.42 | 0.6679 |
| $\Delta(V/U)_{t+1}$ | -0.002 | -1.39 | 0.1636 |
| $\Delta\, skills_t$ | 0.07 | 5.91 | 0.0000 |
| $\Delta\, Skills_{t-1}$ | 0.04 | 7.44 | 0.0000 |
| $\Delta\, Skills_{t+1}$ | 0.01 | 3.16 | 0.0015 |
| $\Delta Female_t$ | 0.30 | 2.45 | 0.0143 |
| $\Delta Female_{t-1}$ | 0.35 | 3.24 | 0.0011 |
| $\Delta Female_{t+1}$ | 0.32 | 2.59 | 0.0095 |
| $\Delta Young_t$ | 0.06 | 1.05 | 0.2905 |
| $\Delta Young_{t-1}$ | 0.10 | 1.43 | 0.1519 |
| $\Delta Young_{t+1}$ | 0.15 | 3.29 | 0.0009 |
| $\Delta\,\mathrm{Re}\,place_t$ | 0.78 | 1.63 | 0.1028 |
| $\Delta\,\mathrm{Re}\,place_{t-1}$ | 0.03 | 0.23 | 0.8136 |
| $\Delta\,\mathrm{Re}\,place_{t+1}$ | -0.50 | -4.13 | 0.0000 |
| $\rho$ | 0.44 | 3.74 | 0.0001 |
| $Max\ Gap$ [vii] | 0.1278 | | |

i- The dependent variable is the outflows from unemployment to employment.
ii- $V$ is the ANZ ads in the three big cities Auckland, Wellington and Christchurch and U is the HLFS number of unemployed workers. Lowercase denotes the rates of vacancy and unemployment (continue).

iii- Skills is the share of employed workers with university and post university qualifications in total employment.
iv- Female is the share of female workers in working age population.
v- Young is the share of workers age 15-19 in working age population.
vi- Replacement ratio is total unemployment benefits to wage of all employed workers fulltime and part-time ratio.
vii- $H_0$: Residuals are white noise. The approximate rejection limits are 1%=0.2881;
5%=0.2404 and 10%=0.2157.

Sketch 1

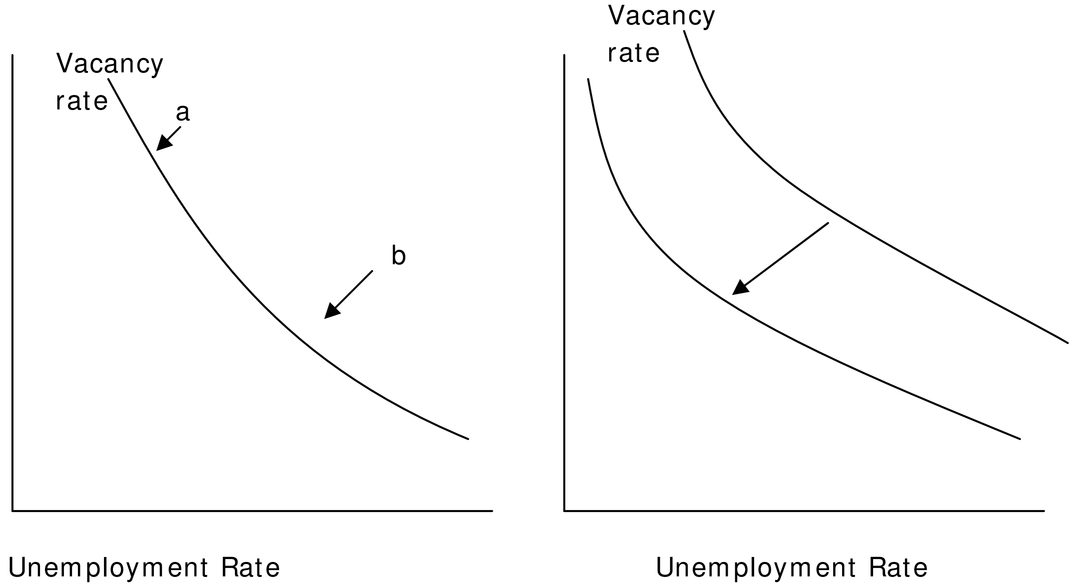



Figure 1

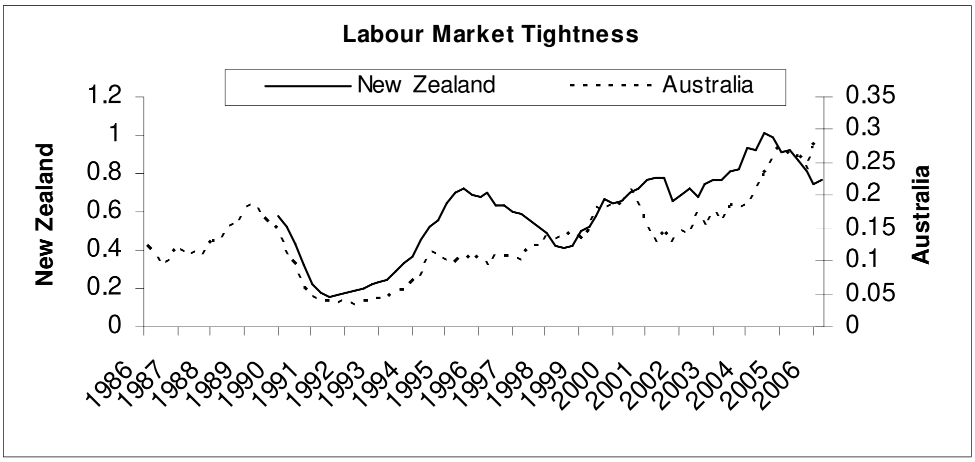


Figure 2

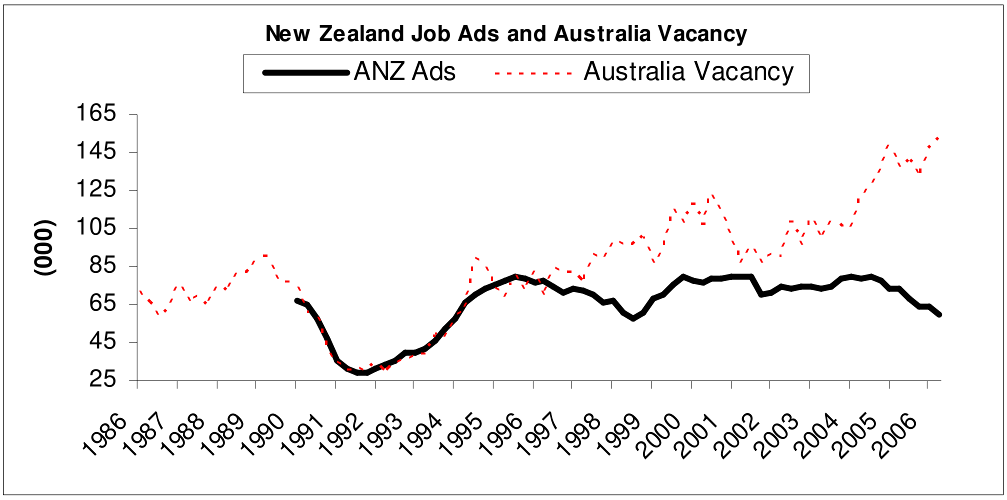



Figure 3

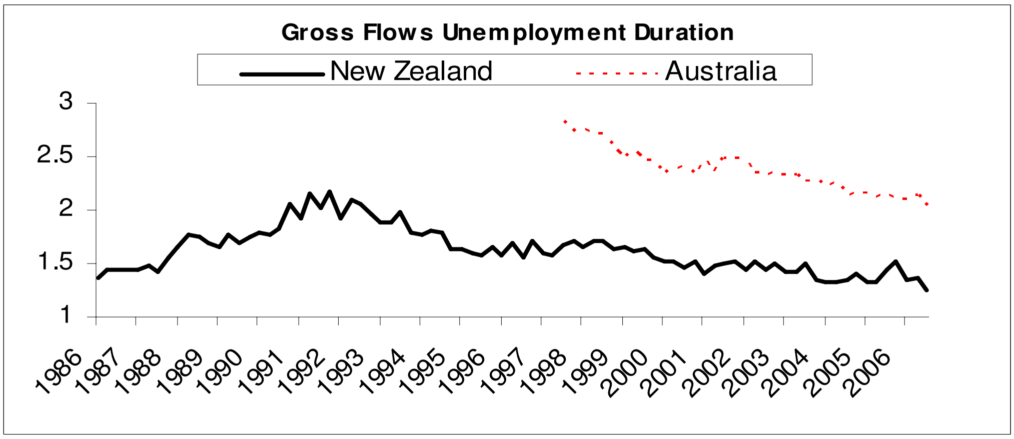



Figure 4

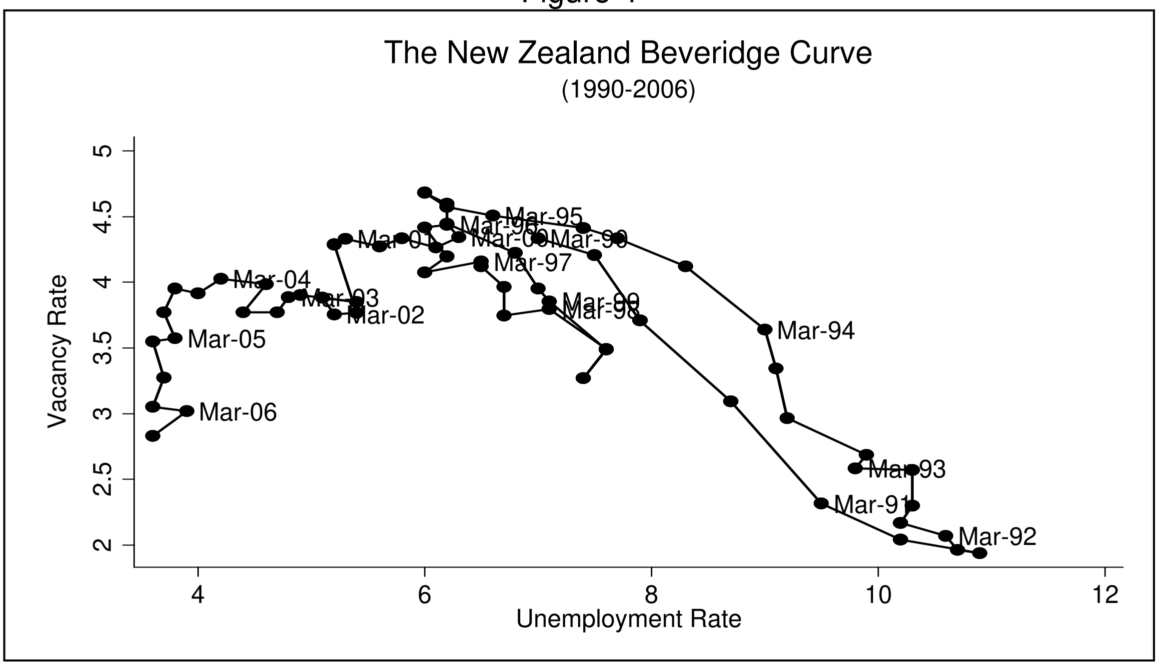


Figure 5

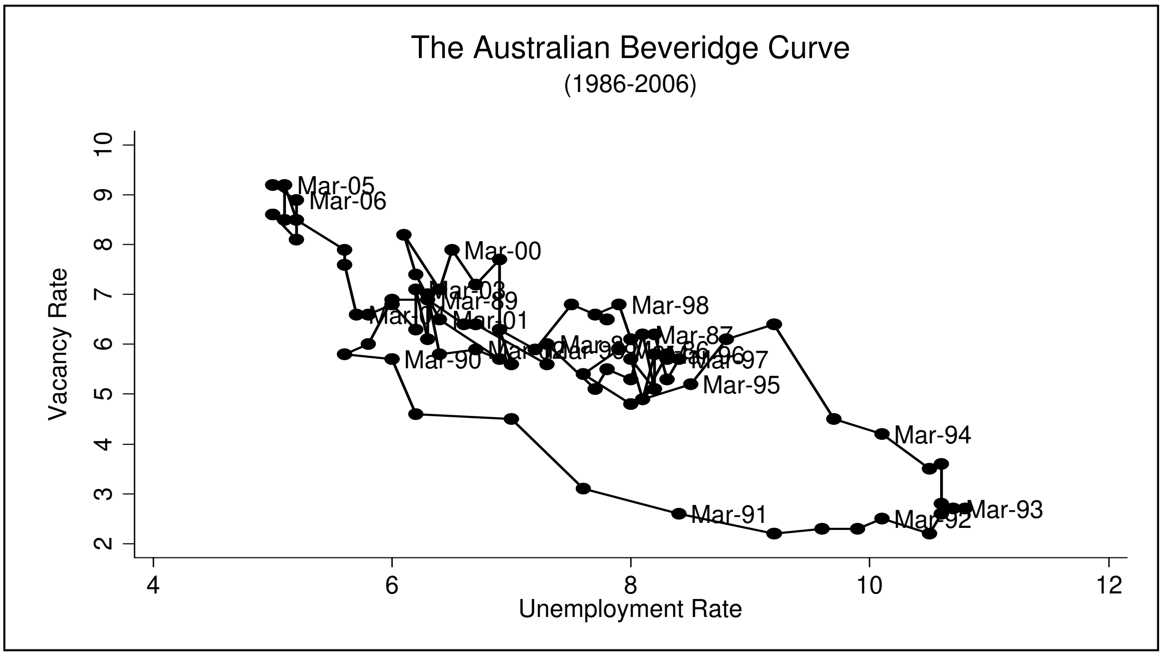



Figure 6

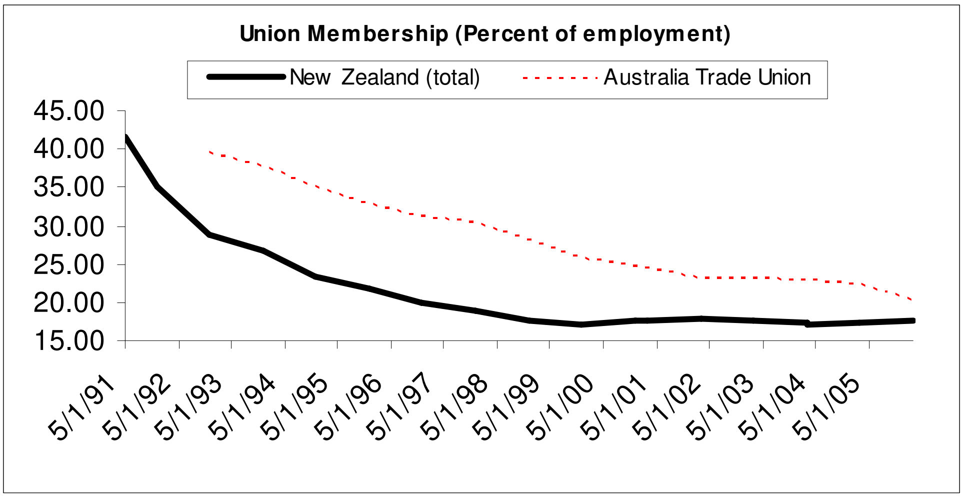



Figure 7

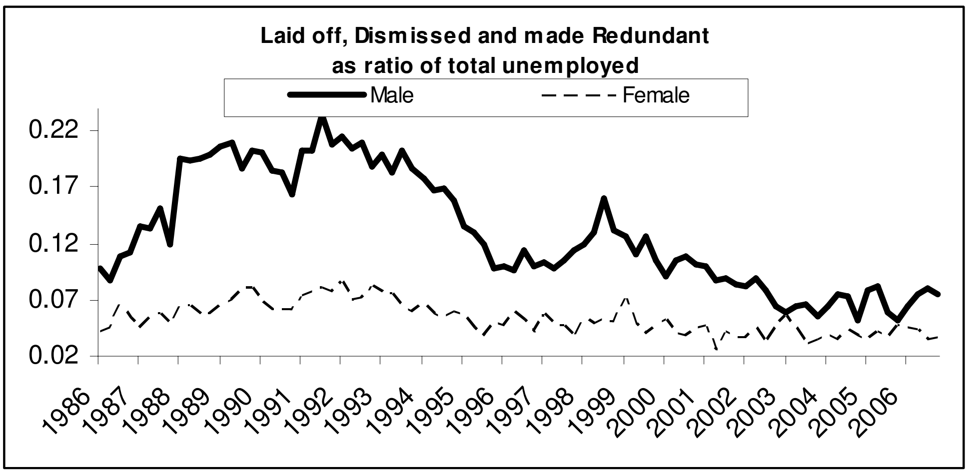


Figure 8

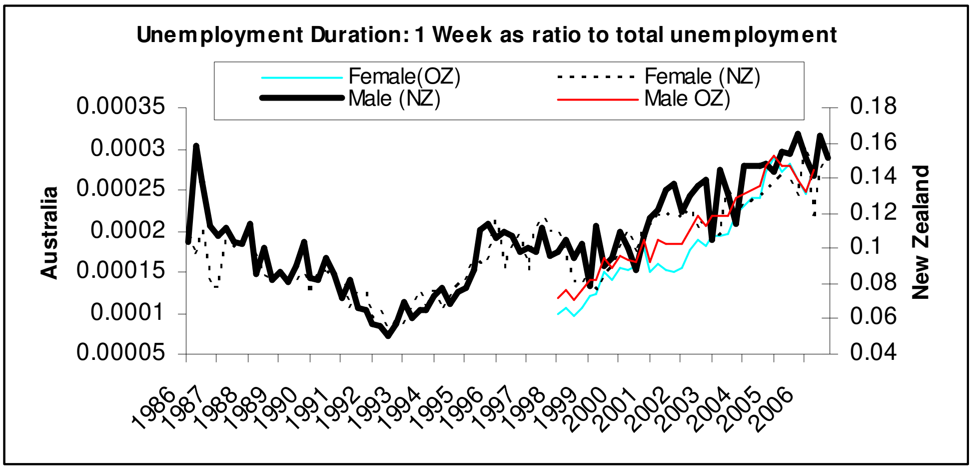



Figure 9

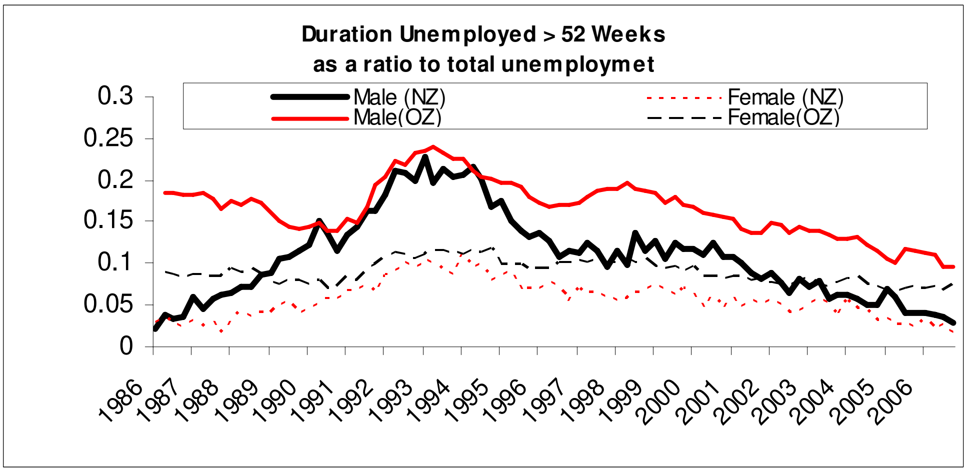



Figure 10

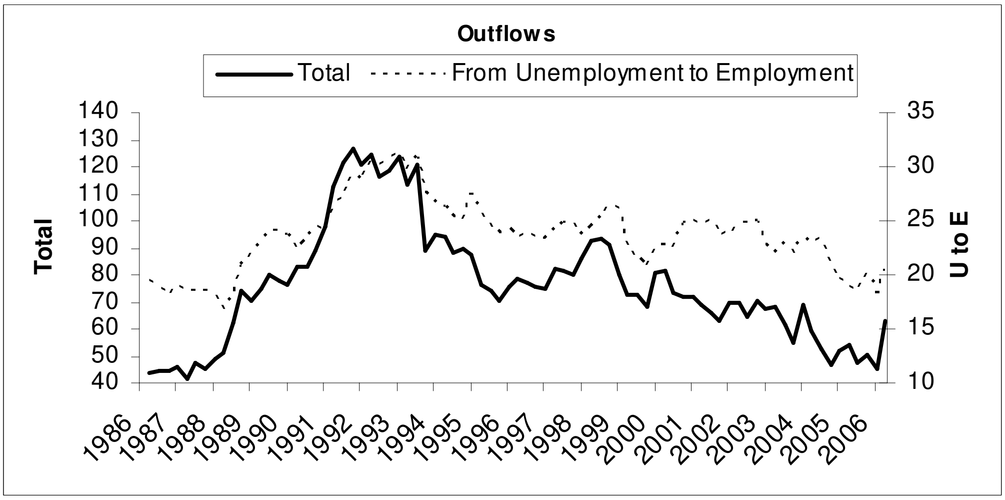


Figure 11

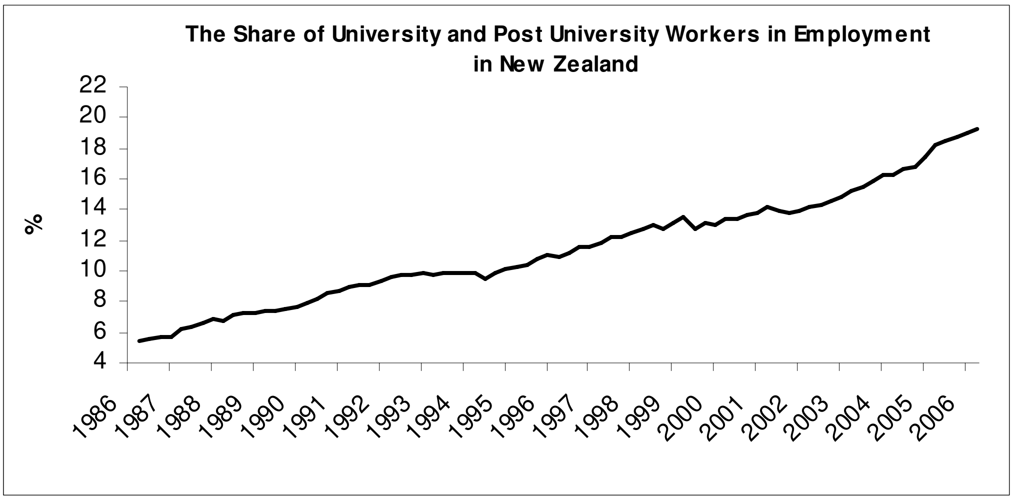



Figure 12

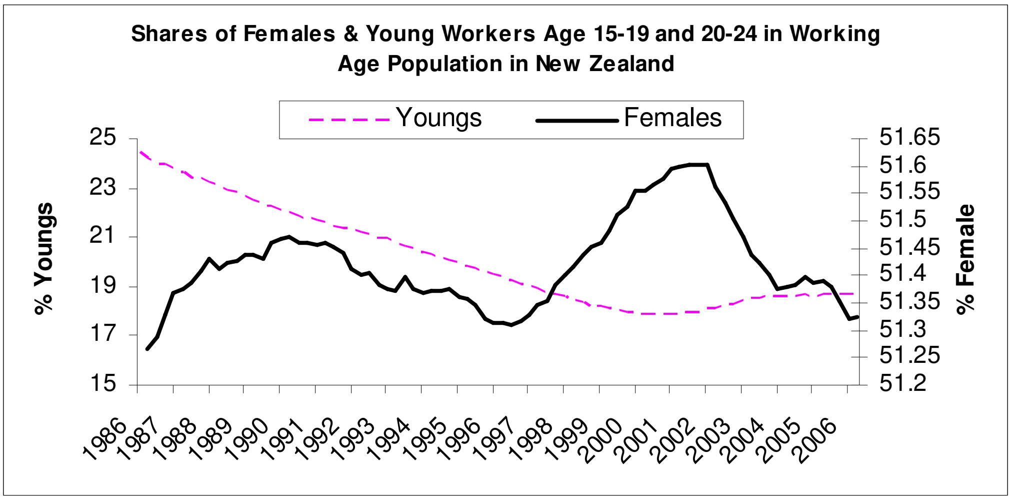



Figure 13

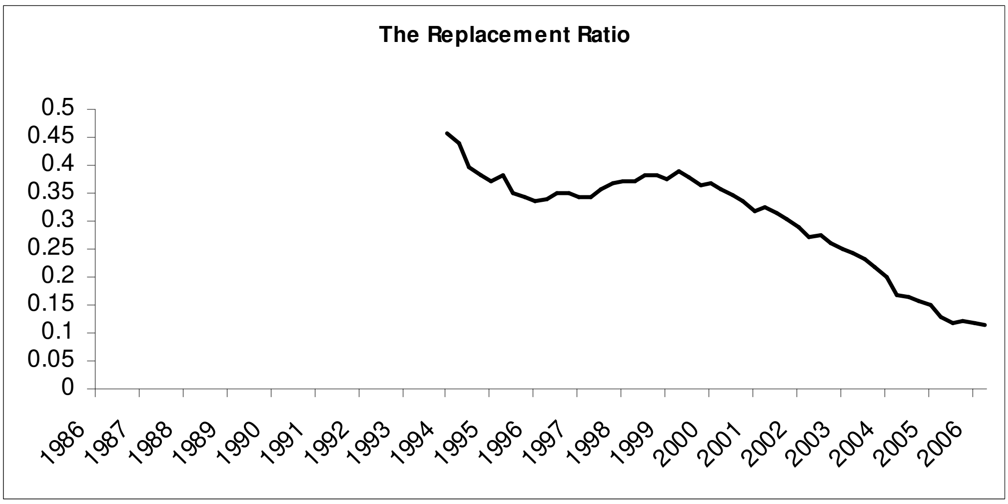


Figure 14

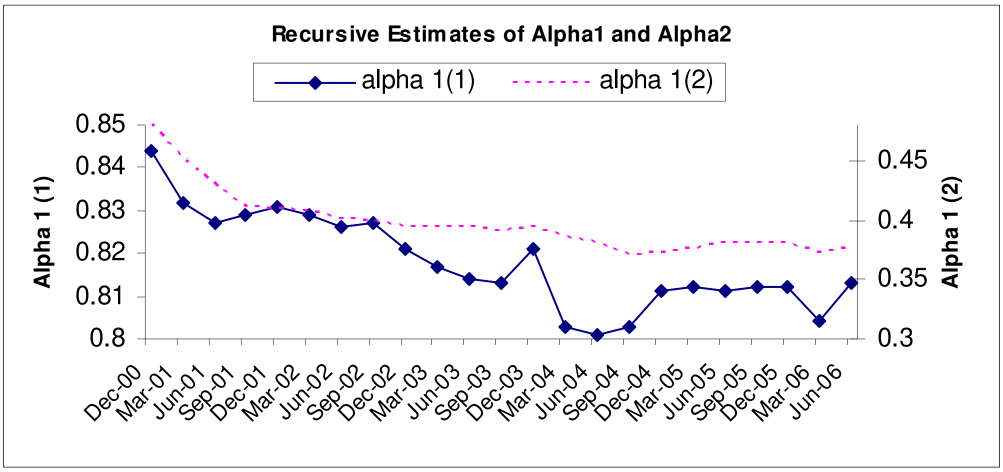



Figure 15

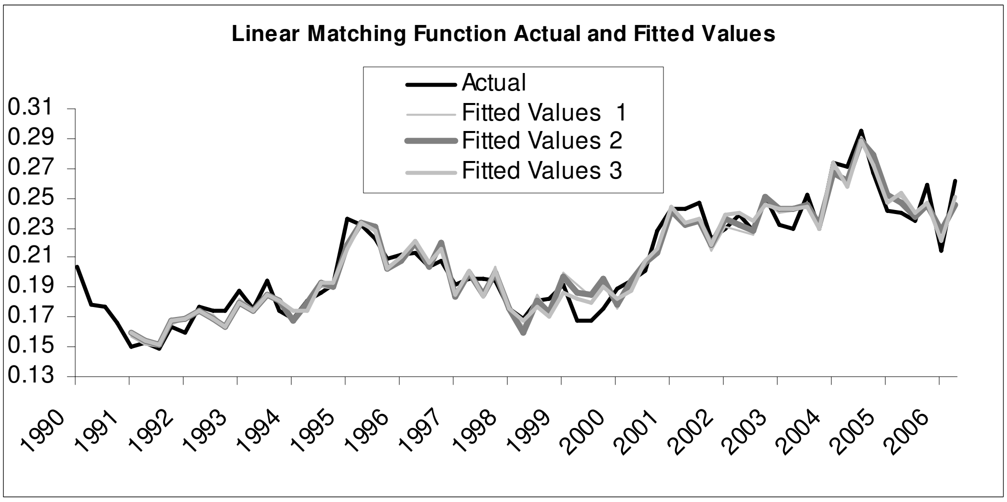



Figure 16

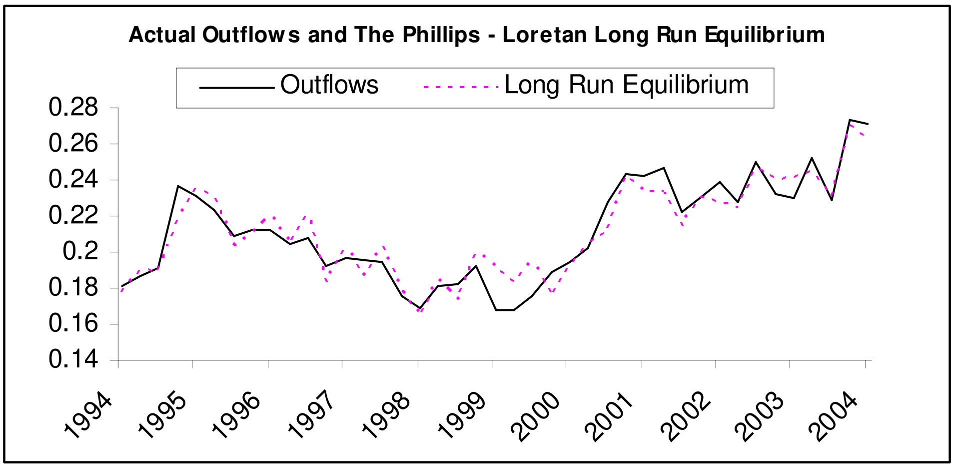
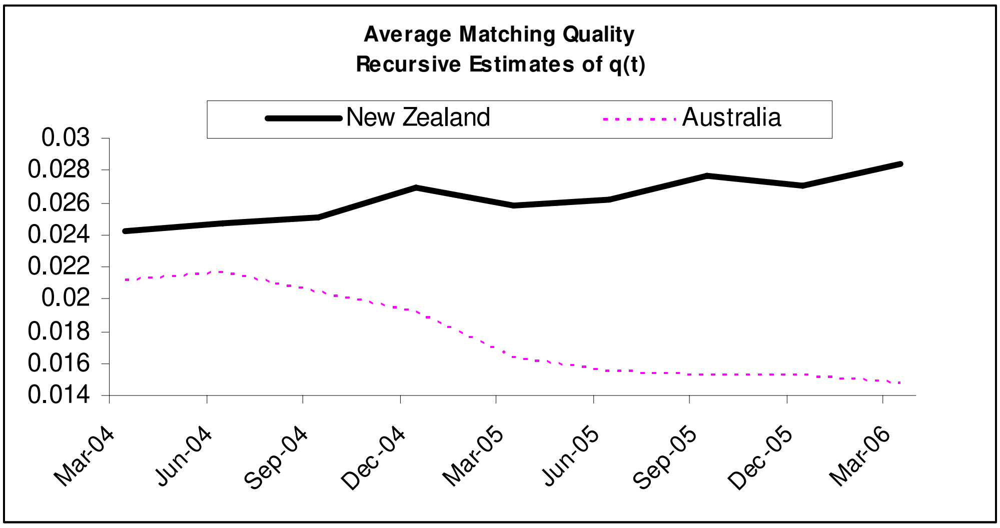


Figure 17


Average Matching Quality
Recursive Estimates of q(t)
New Zealand
Australia
0.03
0.028
0.026
0.024
0.022
0.02
0.018
0.016
0.014
Mar-04
Jun-04
Sep-04
Dec-04
Mar-05
Jun-05
Sep-05
Dec-05
Mar-06

Data Appendix

$M_t$ Matching is defined as:

(1) Total outflows which includes outflows from unemployment to unemployment, from unemployment to employment and from unemployment to not-in-labor force;
(2) Outflows from unemployment to employment only.
(3) The rate of outflows is outflows / number of unemployed.

Source: Household Labor Force Survey (HLFS).

$U_t$ is the total number of unemployed workers.
Source (HLFS).

$V_t$ is job ads. We use job ads for Auckland, Wellington and Christchurch only.
Source (ANZ Bank).

$u_t$ is the unemployment rate.
$v_t$ is the vacancy rate, where job ads for the big three cities deflated by HLFS number of employed workers for whole economy. We tried to deflate by employment in the three big cities, and also examined ANZ vacancy rate data, but found no significant differences.

$E_t$ is total full time employment
Source (HLFS)

$Skill_t$ is defined as the share of workers who have university and post university qualifications in total employment.
Source (HLFS)

$Female_t$ is the share of full time female workers in working age population.
Source (HLFS)

$Young_t$ is the share of workers aged 15-19 and 20-24 in working age population.
Source (HLFS)

$\mathrm{Re}\,place_t$ is the replacement ratio defined as total unemployment benefits to wages. The unemployment benefit data are from the Ministry of Social Development. Wages is hourly wages times the number of hours worked.

The Australian data are from the Australian Bureau of Statistics website.

[i] The growth rate is, e.g., $(\ln x_{1992} - \ln x_{1986}).100$. New Zealand changed the Employment contract Act of 1991 to the Employment Relations Act in 2002. There are subtle differences to promote collective bargaining and good faith. It has been argued that one should split the sample in 2002. We do not do that because the sample would be small and because various evaluation studies showed that the new Act has not affected the performance of the labor market(Waldegrave, Anderson and Wong, 2003).

[ii] See also, Fontaine (2007) on the matching function and social networks, Kagasharju *et al.* (2005) on matching function and the use of disaggregated data, Kano amd Makoto (2005) for evidence on Japan.

[iii] Petrongolo and Pissarides (2001) provide a survey of the literature and argue that CRTS has wide empirical support. Increasing returns to scale gives rise to the possibility of multiple equilibrium. It implies that hiring is twice as high in a labor market that is twice as big.

[iv] For New Zealand see Silverston (2001) and (2006). For Australia see De Francisco (1999).

[v] Petrongolo and Pissarides (2001) provide a list of problems with matching functions.

[vi] Before we estimate the matching unction we tested all variables for unit root using a variety of common unit root tests with different specifications and lag specifications. We tested these lags thoroughly using a variety of common information criteria. We could not reject the unit root hypothesis in job ads, unemployment and the outflows from unemployment to employment. These results may reflect the weak powers of these tests. We tested the data again for a shorter sample, 1994Q1 to 2006Q2 to avoid the break in the data. We still could not reject the unit root hypothesis.

[vii] Petrongolo and Pissarides (2001) do not report tests of the residuals.

[viii] Again, a variety of commonly used tests for unit roots, different model specifications, and different information criteria are used to test the variables. There is a strong evidence of unit roots in the data. Although the tests have low powers, the data exhibit visible trends. For this reason I will assume that the data have unit roots. To test for no cointegration I regressed the dependent variable on a constant, trend, and the contemporaneous vacancy rate, the unemployment rate, the ratio of vacancy to unemployment, *skills*, *female, young and the replacement ratio* (as defined above), and tested the residuals for unit root. Then I estimated an error correction regression and tested whether the error correction terms is equal to zero. I found the error correction term to have a very high *t* statistics, -4.7, which implies that the variables might very well be cointegrtaed. The OLS estimated reported in table 4 are most probably super-consistent.

[ix] The estimator takes into account unit roots, cointegration, the serial correlation of the residuals and the endogeneity problems.

[x] Carrol et al. (2002) used disaggregated data from LEED (Linked employee-employers data) and reported an average estimate of 15.3 percent over the period 1994-2001. They measure the job destruction rate as the total decrease in employment across contracting and dying firms relative to average total employment. $\Delta e_t^d = \sum_i [I(E_{it} > E_{it})(E_{it-1} - E_{it})] / \overline{E}_t$ , where $I$ is an indicator function, which is equal to one if the expression in parentheses is true, and zero otherwise. They also reported that the estimate varies across industries, 12.8 to 27.7, which averaged to be 18.98 percent. The estimate also varies with the firm's size, 22.3 percent for a firm with 1 to 5 workers and 10 percent for a firm with more than 100 workers, averaging 15.2. The estimates reported in this paper, which uses a completely different data set, highly aggregated, and a different model, are almost the same as the estimates reported using the LEED (Linked Employer – Employee Data) disaggregated data.