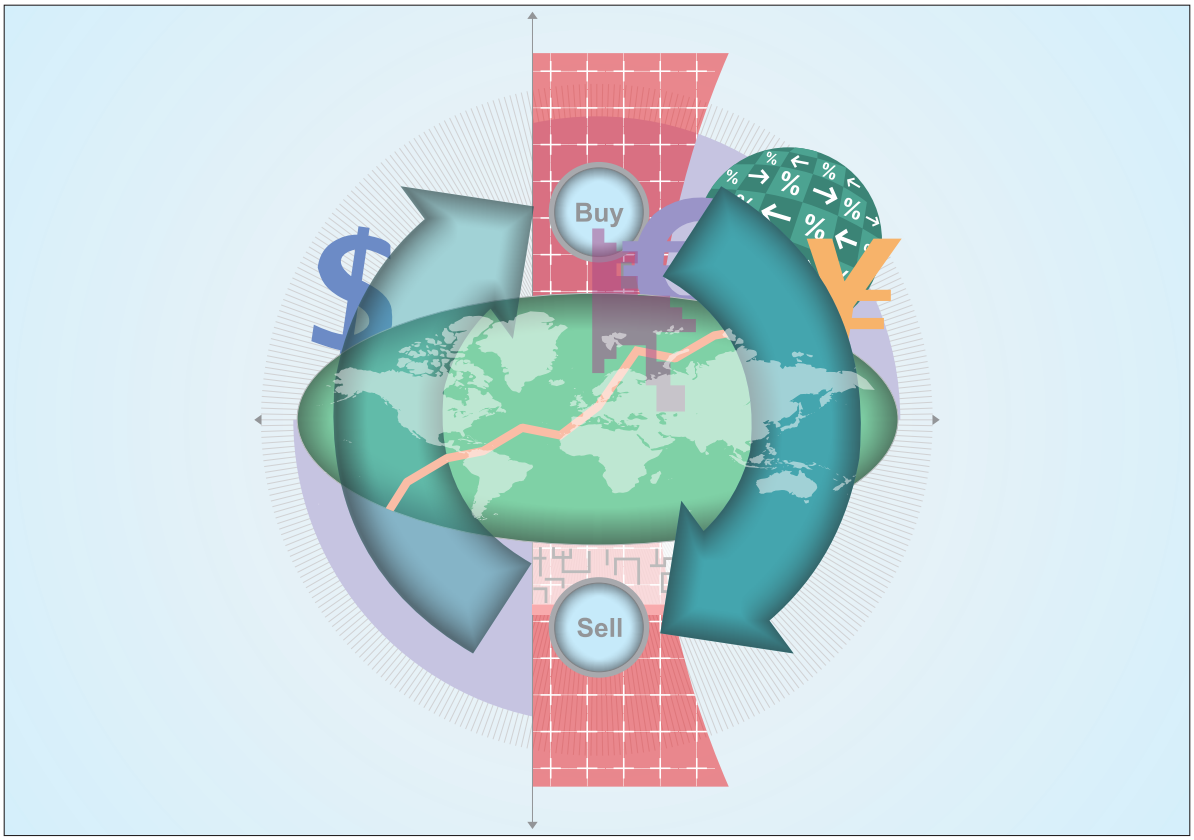

The International Journal of Applied Economics & Finance

ISSN 1991-0886

science alert

ANSInet
an open access publisher
http://ansinet.com

The International Journal of Applied Economics and Finance 5 (3): 157-166, 2011
ISSN 1991-0886 / DOI: 10.3923/ijaef.2011.157.166

Matching Function: Estimations using JOLTS

A. Mandal
Department of Economics, Siena College, 515 Loudon Road, Loudonville, NY-12211, USA

ABSTRACT

The study estimates a matching function for the US non-farm sector using the Job Opening and Labor Turnover Survey (JOLTS) data. In the recent years, matching function has emerged as the workhorse of modern labor search theory. It enables the modelling of frictions in otherwise conventional economic models, with minimum of added complexity. In theoretical search framework, it is assumed that matching function has constant returns to scale. To verify the returns to scale character of the matching function empirically, monthly JOLTS data has been used from December 2000 to March 2009 to estimate a matching function for the US. The study found that the returns to scale of the matching function vary according to business cycle. The close to constant returns to scale matching function only obtained for the non-recessionary time period. The study concluded that the functional form of the matching function may not be stable over time and one need to take into account business cycle fluctuations and its impact on the functional form of the matching function while understanding labor and worker flows in an economy.

Key words: Matching function, business cycle, search theory, unemployment, recession

INTRODUCTION

Matching function is the workhorse of modern labor search theory. The standard treatment of matching models remains (Pissarides, 2000)[1]. In a decentralized market, workers look for the right job and employers look for the right worker, but each search for varying degree of intensity and success. The matching function summarizes the trading technology between the employers and the potential employees. The primary idea behind matching function is to model this complex search procedure through a simplified well-behaved function. The matching function gives the number of jobs formed at any moment in time in terms of the number of workers looking for jobs, the number of firms looking for workers and a small number of other variables. At given inputs, variations in job matches reflect changes in the intensity of frictions that characterize labor market trade. With stronger frictions, the labor market becomes less effective in matching unemployed workers to available vacancies and the resulting matching rate is reduced (Pissarides, 2000; Blanchard and Diamond, 1989). The attraction of matching function is that it enables the modelling of frictions in otherwise conventional models, with minimum of added complexity.

A matching function generally takes the following Cobb-Douglas functional form.

$$M = M(U,V) = AV^{\alpha}U^{\beta}$$

where, M is the number of jobs formed during a given time interval, U is the number of unemployed workers looking for work and V the number of vacant jobs. We assume that M(U,V) is increasing in both arguments and concave, e.g., $M'(\theta)>0$ and $M''(\theta)<0$. Other restrictions usually imposed are $M(0,V)=M(U,0)=0$.

[1]See Rogerson *et al.* (2005) for recent survey of the labor-search literature

One of the main concerns in studying the aggregate matching function is to identify the level of returns to scale. In the search and matching literature, it is assumed that matching function has constant returns to scale (CRS) ($(\alpha+\beta) = 1$). Diamond (1982) and Pissarides (1986) showed that increasing returns to scale is consistent with search externalities and multiple equilibria.

For the US, limited numbers of studies are available on the estimates of matching function. First attempt to estimated a matching function is made by Blanchard and Diamond (1989), then consequently Warren (1996) and Bleakley and Fuhrer (1997). These studies generally accept the assumption of a log-linear function with constant returns to scale. An exception is Warren (1996), who estimates a translog matching function by using the monthly US manufacturing data and finds increasing returns to scale. Similar matching function is estimated for other countries[2].

In order to estimate a matching function, unemployment, vacancies and hires data is needed. In most countries, though fairly good data on unemployment is widely available, but data on hires and vacancies are often nonexistent. In the US traditional proxy for vacancy is the Help Wanted Index (HWI) prepared by the Conference Board. It is collected on monthly basis from the counts of job advertisements in major newspapers. However, the level of newspaper help-wanted advertisement varies both by labor market conditions and the extraneous factors. For example factors not directly related to labor demand are changes in occupational composition of employment (white-collar jobs are more likely to be advertised than blue-collar jobs) and the introduction of equal employment opportunity requirements (Shimer, 2005). Because of the restrictions imposed by the unavailability of reliable data, only a few limited efforts are made to estimate the matching function for the US. However since December 2000, Bureau of Labor Statistics introduced a new data series called JOLTS. This is an attempt by BLS to collect data on hirings, separations and job openings using a nationwide sample of establishments. This new series completes the labor market picture by collecting data from businesses to measure labor demand and job turnover.

MATERIALS AND METHODS

JOLTS data from December 2000 to March 2009 has been used to estimate the matching function for the US Currently, JOLTS is the only existing data source to measure vacancies, hires and separations at the establishment level at a regular monthly frequency in the US. This is an ideal data source to estimate matching function for the US. The JOLTS program publishes monthly estimates of vacancies, hires and separations, with separations broken into quits, layoffs and discharges, and other separations. The data start in December 2000 and are updated monthly. The aggregate estimates are available nationally and for four major regions by 2-digit North American Industry Classification System (NAfCS). Prior to December 2000 JOLTS data is not available and the choice of March 2009 accounts for the fact the US already gone through 15 months of recession since December 2007. All the data is seasonally adjusted to remove any seasonal variations.

The primary unit of observation for the JOLTS survey is the establishment, which covers the operations of firms at a single physical location. It covers nonfarm payrolls, which implies that employment estimates generally exclude self-employed individuals and non-profit organizations not covered under the state unemployment insurance program. A sample of roughly 16,000 establishments surveyed each month. The data is weighted so that its employment estimates match

[2]See Feve and Langot (1996) for France, Van-Ours (1991) for Netherlands, Burda and Wyplosz (1994) for France, Germany, Spain and UK, Berman (1997) and Yashiv (2000) for Israel and Mumford and Smith (1999) for Australia. For a survey on matching function, see Petrongolo ang Pissarides (2001)

those of the Current Employment Statistics (CES) survey. At the micro level, the data can also be matched with BLS Quarterly Census of Employment and Wages (QCEW) data (Faberman, 2005).

According to BLS, the definition of the key elements of JOLTS is as follows:

- **Employment:** JOLTS define Employment as all persons on the payroll who worked during or received pay for the pay period that includes the 12th of the month. This definition is consistent with other BLS establishment-based programs
- **Job Openings (Vacancies):** JOLTS define Job Openings as all positions that are open (not filled) on the last business day of the month
- **Hires:** JOLTS define Hires as all additions to the payroll during the month
- **Separations:** JOLTS define Separations as all employees separated from the payroll during the calendar month

The monthly data on unemployment is obtained from the Current Population Survey (CPS) of the US Bureau of Labor Statistics. In order to maintain symmetry with JOLTS data, we use monthly unemployment data for the period December 2000 to March 2009. The series is seasonally adjusted to remove the seasonal variations.

According to matching and search theory, whenever an employed worker is separated from a job; he joins the pool of unemployed workers. Then matching for new job happens from this updated pool of unemployed. Standard matching function does not account for the fact that there are job to job transitions. However, the relative importance of job-to-job transitions increased dramatically in recent decades: between 1975 and 2000, the rate of job-to-job transitions increased by 59% and the rate of employment to unemployment transitions declined by 47% (Stewart, 2002). This means that job-to-job transitions is an important means of reallocating labor towards its more productive uses as are the transitions of workers through unemployment.

In order to ensure that estimates are consistent with theory, we adjusted the hiring data for job-to-job transitions. Though, CPS or JOLTS, do not give any standard information regarding the job-to job-flows, but information regarding quits in JOLTS and the number of unemployed because of job leaver in CPS, can be used to estimate the job-to-job transitions. Quits in JOLTS are employees who left voluntarily except for retirements or transfers to other locations. So assumption is employees who quit either going for a new job or join the pool of unemployed labors. Subtracting the number of unemployed workers because of job leavers from the quits, we estimate job-to-job transitions. Net Hires is defined as total hires reported by BLS minus the job-to-job transition (Fig. 1)[3].

In Fig. 1, both total hires and the job-to-job transition is procyclical. During downturns, vacancy creations drops and hence job-to-job transitions declines because of the drop in probability of finding a job. The data shows that Net hire series is acyclical. The business cycle fluctuations in hires are primarily driven by job-to-job transitions during the period under study.

The pool of unemployed workers is adjusted for the unemployed workers who consider themselves as having a job. Unemployed is defined as the total number of unemployed workers[4] minus the job losers on temporary layoff and the job losers who completed some temporary jobs (Fig. 2). Unemployment is counter cyclical. Adjusted unemployment numbers are counter cyclical as expected.

[3]According to my estimates, job-job transitions accounts for on an average 37.33% of the total hirings every month. This figure varies considerably from 22.63 to 46.30%

[4]Pool of unemployed workers is the usual U3 definition of unemployed as provided by the BLS

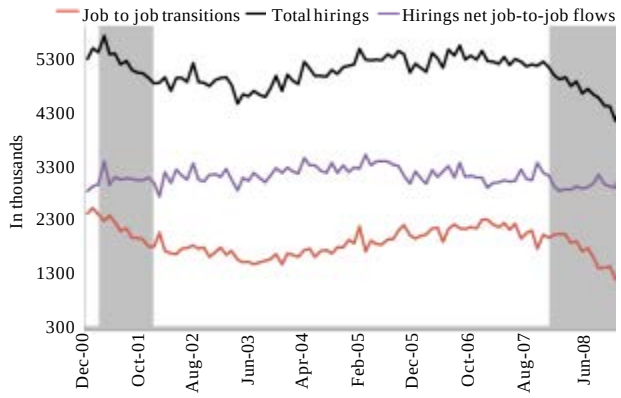

Fig. 1: Job-to-job transsition, total Hirings and Hirings Net of Job-to-Job flows Dec. 2000-Mar. 2009. Source: JOLTS and CPS. The shaded region shows the recession years

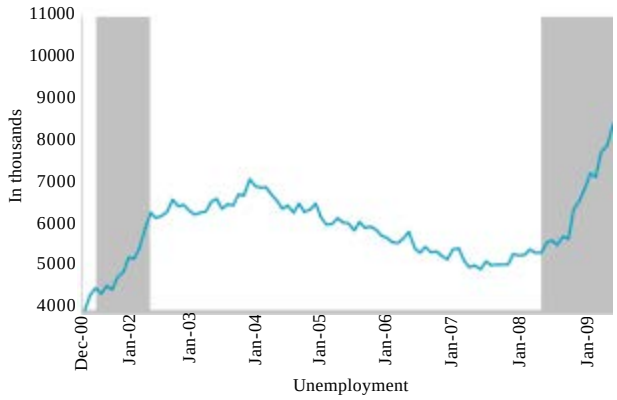

Fig. 2: Unemployment Dec. 2000-Mar. 2009. Source: Bereau of Labour Statistics. The shaded region shows the recession years

Based upon literature, following Cobb-Douglas function estimated:

$$\log H_t = \log A + \alpha \log V_t + \beta \log U_t + \lambda_1 t + \lambda_2 t^2 + \varepsilon_t \quad (1)$$

where, ε_t[5] is the random error term with normal distribution and mean zero, variance σ^2 and t is the time trend. H_t is the number of Net Hires, V_t is Vacancies created per month and U_t is the adjusted number of unemployed. All the numbers are in levels. The returns to scale are estimated by adding regression coefficients of V_t and U_t. If $(\alpha+\beta)>1$, then we have increasing returns to scale, for $(\alpha+\beta) = 1$constant returns to scale and $(\alpha+\beta) <1$ decreasing returns to scale.

The period under study is marked by substantial ups and downs in the economy within a very short period of time. In this period, the US experienced two business cycle downturns, first one lasted for eight months between the March 2001 and the November 2001 and the second one between December 2007 and June 2009[6]. Since business cycle fluctuations have important

[5]For AR(1) specification, ε_t follows $\varepsilon_t = p\varepsilon_{t-1} + u_t \sim N(0,\sigma^2)$. AR(1) specification has been used to improve upon the Durbin-Waston statistic

[6]Based upon National Bureau of Economics Research (NBER) dating of US business cycles

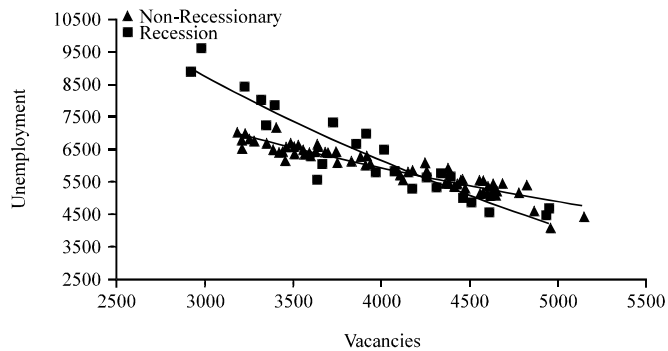

Fig. 3: Beveridge curve Dec. 2000-Mar 2009. Source: JOLTIS and CPS

implications on the movements of hires, vacancies and unemployment, it is important to take in to account business cycle fluctuations while estimating a matching function. Beveridge curve shows the correlation between vacancies and unemployment. In order to visualize the changing nature of relationship between vacancy and unemployment, we scatter plot the two variables. This scatter plot showing vacancy and unemployment is called the Beveridge Curve in the literature. Beveridge curve for the recessionary and the non-recessionary periods are plotted in Fig. 3. Clearly the curves in two periods have different slopes. The Beveridge curve for the recessionary period is steeper than the one during non-recessionary period. To estimate the matching function, it is important to take into account of these differences. One way is to estimate using dummy variable technique. Since both the slope and the constants are significantly different, hence we use the method of interactive dummy to estimate the matching function. The econometric specification is:

$$\log H_t = \log A + \alpha \log V_t + \beta \log U_t + \gamma 1 dum + \gamma 2 dum * \log V_t + \gamma 3 dum * \log U_t + \varepsilon_t \quad (2)$$

where, dum =1 for recession time periods, otherwise dum = 0.

To check the robustness of the result, we estimate the model using other specifications. Technically hires can be made from the pool of unemployed workers, pool of workers who are looking for jobs while working and the pool of workers from the out of labor force. Though hires have been adjusted for the job-to-job transitions, but hires are also made from the people out of labor force. According to Blanchard and Diamond (1989), about 40 percent of the hires in the period between 1970 and 1981 were from the out of labor force. CPS collects information on the number of working age people who are out of labor force and also gives information on the willingness of the people to take a job. In order to account for the hires from the out of labor force, we estimate the following specification:

$$\log H_t = \log A + \alpha \log V_t + \beta \log U_t + \gamma NL_t + \varepsilon_t \quad (3)$$

where, NL_t refer to persons who have searched for work during the prior 12 months and were available to take a job during the reference week of BLS survey.

RESULTS

The job-to-job transitions were estimated using the secondary data available from Current Population Survey (CPS) in the U.S. Bureau of Labour Statistics. The estimated job-to-job

Table 1: Stationarity test

	Level			First difference		
	ADF	PP	KPSS*	ADF	PP	KPSS*
Ht	0.2052	0.3005	0.2257	-10.7194	-23.3103	0.0627
Ut	1.6246	1.9951	0.1484	-3.8818	-8.0181	0.3444
Vt	-1.9196	-1.5175	0.1523	-13.6197	-13.0184	0.3053
Nlt	1.7292	1.5752	0.1388	-9.3617	-13.2743	0.2400

ADF: Augmneted Dickey-Fuller Test (5% level of significance is -3.4563) PP: Phillips-Perron Test (5% level of significance is -3.4558) KPSS: Kwiatkowski-Phillips-Schmidt-Shin (5% level of significance is 0.463000). * Under KPSS test, Null hypothesis = Series is stationary, Ht = Net Hires per month Ut = Number of unemployed per month, Vt = Vacancies per month, NLt = People who have searched for work during the prior 12 months

transition were shown in Fig. 1. During recession the available job options decreases and hence workers prefer to stay in the job rather than moving from one job to another. So we observed in Fig. 1, job-to-job transition decreased during the period of economic downturns (shaded area in the figure). Figure 2 showed the monthly unemployment since December 2000. Clearly unemployment is cyclical, rising during recessions and declining during economic booms. Figure 3 showed the relationship between unemployment and vacancy popularly known as Beveridge Curve. The Beveridge curve was downward sloping because periods of higher unemployment were marked by lower vacancy and vice versa. We separately plot the Beveridge curve for the recessionary and the non-recessionary time period. The plot shows that the recessionary and the non-recessionary time period had separate slope for Beveridge curve. Clearly the relationship between vacancy and unemployment vary according to business cycle.

For any time series analysis, first step is to check stationarity of a series. The stationarity test results were shown in Table 1. Hires, Unemployed and Vacancy were all non-stationary with integrated of order 1. Since, at least two series were non-stationary of the same order, hence there was possibility of estimating a cointegrating relation.

Regression results for Eq. 1 along with the Augmented Engle-Granger cointegration tests were shown in Table 2[7]. Various lead and lag[8] structures were applied to the variables to account for the different timings of data collection. However, the best results were obtained by using the contemporaneously timed data across all variables[9].

[7]Results of stationarity test are given in Table 1. We tested for stationarity of the data using Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) test. For the applications of stationarity tests see Lohano and Soomro (2006) and Sahin *et al*. (2007). All the series are non-stationary at 5% level of significance. At the same time, all the series are integrated of order 1 I(1). Hence, we estimate a cointegrating regression (see Engle and Granger (1987), Dickey and Fuller, 1981). For applications of cointegrating regression see Adam (2011), Ong and Muzafar (2008)

[8]Refer to Table (3) for regressions with lagged variables. Explanatory variables Log (Vt) and Log (Ut) turn out to be insignificant for all the specifications

[9]Since hires are flow variable and vacancies and unemployment are stock variables, the use of contemporaneous values of hires, vacancies and unemployment raises the possibility of downward bias in the least-square estimates of returns to scale (Blanchard and Diamond, 1989,). In recognition to this problem, Blanchard and Diamond used various instruments for unemployment and vacancies. However, Hall in his comments on Blanchard and Diamond expressed considerable scepticism about the validity of these instruments. Therefore instruments have been avoided in the present study

Table 2: Estimation of cobb-douglas matching function for US non-farm sector

Log (H_t) dependent variable	Const.	Log (V_t)	Log (U_t)	Time trend (t)	Time trend square (t^2)	AR (1)	R^2	Adj R^2	D-W	AEG test*	Return to scale
1	3.0988	0.2681	0.3130	0.0027	-0.00003		0.2984	0.2689	1.4776	-7.5681	0.5811
	(1.7937)	(2.5353)	(3.1025)	(4.6085)	(-5.7642)						
2	5.4858	0.1358	0.1701	-0.000446		0.4514	0.2417	0.2094	2.2781	-11.3965	0.3059
	(3.2243)	(1.3016)	(1.6314)	(-1.3548)		(4.9693)					
3	4.2002	0.1998	0.2511	0.0027	-0.000032	0.274265	0.3248	0.2885	2.0945	-10.3349	0.4509
	(2.4593)	(1.9224)	(2.4626)	(3.2412)	(-3.9597)	(2.7286)					

#D-W: Durbin Watson Statistic (at 5% D-W critical values with 100 observations and 4 explanatory variables are 1.592 for lower level and 1.758 for upper level), *AEG: Augmented Eugle-Granger Test for Cointegration (AEG critical value at 5% level of significance is -1.9439). t-statistic in parenthesis. At 5% level of significance, critical value for t-satistic is 1.96

Table 3: Estimation of cobb-douglas matching function for US non-farm sector using recession dummy

Log (Ht) dependent variable	Coust	Log(V_t)	Log(U_t)	Time trend (t)	Time trend square (t^2)	Dum	Dum* Log(V)	Dum* Log(U)	AR(1)	R^2	Adj R^2	D-W#	AEG test*	Returus to scale
1	3.0297	0.2729	0.3157	0.00303	-0.000037	0.007695				0.3001	0.2629	1.4739	-7.5485	0.5886
	(1.7405)	(2.5589)	(3.1116)	(3.5054)	(-4.0463)	(0.4791)								
2	5.2933	0.1419	0.1867	-0.00034		-0.0319			0.3508	0.2678	0.2284	2.1792	-10.8797	0.3286
	(3.0732)	(1.3463)	(1.7991)	(-1.1565)		(-2.1222)			(3.6417)					
3	4.0877	0.2062	0.2568	0.0032	-0.000037	0.0116			0.2792	0.3271	0.2833	2.0959	-10.336	0.463
	(2.3636)	(1.9601)	(2.4926)	(2.5996)	(-2.9397)	(0.5622)			(2.7594)					
4	0.8229	0.3174	0.5313	0.000128		9.8488	-0.5067	-0.6539	0.3682	0.3346	0.2834	2.1607	-10.6769	0.8487
	(0.3697)	(2.6366)	(3.4789)	(0.3584)		(2.7846)	(-2.3281)	(-3.0095)	(3.6659)					
5	1.4813	0.3343	0.4350	0.0028	-0.000032	7.5165	-0.4652	-0.4206	0.286129	0.3602	0.3034	2.11	-10.4069	0.7693
	(0.6570)	(2.7756)	(2.7715)	(2.0153)	(-2.0214)	(2.0526)	(-2.1578)	(-1.7742)	(2.7628)					

#D-W: Durbin Watson Statistic (at 5% D-W critical values with 100 observatious and 5 explanatory variables are 1.571 for lower level and 1.78 for upper level). *AEG: Augmented Engle-Granger Test for Cointegration (AEG critical value at 5% level of significance is -1.9439). Dum: Recession dummy t-statistic in parenthesis. At 5% level of significance, critical value for t-satistic is 1.96

The estimates are sensitive with respect to time trends, especially the squared time trend. The signs of the coefficients of Log(U_t) and Log(V_t) are all positive as expected. The best fit is obtained both in terms of R^2 and adjusted R^2 for specification 3 which includes a squared time trend term and the errors follow an AR(1) specification.

None of the specifications have constant returns to scale. All the estimates has $(\alpha+\beta)<1$, which implies decreasing returns to scale. Though decreasing returns to scale is neither theoretically, nor empirically implausible, but it raises question regarding the plausible divergence from prior studies.

To account for the fact that business cycle fluctuations may impact the matching function, we estimated Eq. 2 with recession dummies. The estimation results are shown in Table 3. The signs of the explanatory variables are positive as expected. All the parameters except for the constant terms are significant at 5 % level of significance. In the model with interaction dummies e.g., specification 4 and 5, the returns to scale turns out to be between 0.7693 and 0.8487. If recession is taken in to account, the aggregate matching function were very close to constant returns to scale.

To check for the robustness of the model, we estimated Eq. 3. The results of the regression were shown in Table 4 for the overall, recessionary and the recessionary and the non-recessionary periods. For the overall time period, returns to scale was 0.5179, whereas for the non-

Table 4: Estimation of cobb-douglas matching function for US non-farm sector with nlt

Log (Ht) dependent variable	Const	Log (V_t)	Log (U_t)	Log (NLt)	Time trend (t)	Time trend square (t^2)	R^2	Adj R^2	D-W#	AEG test*	Returns to scale
All periods	2.5057	0.2797	0.2382	0.1596	0.0021	-0.000029	0.3223	0.2862	1.6386	-8.2604	0.5179
	(1.4419)	(2.6724)	(2.2088)	(1.8198)	(3.1274)	(-4.7548)					
Non Recessionary period	-1.3084	0.3701	0.4383	0.3439			0.2773	0.2454	1.8007	-7.774	0.8084
	(-0.5544)	(3.1335)	(2.7565)	(3.8383)							
Recessionary period	9.0402	-0.1419	0.1066	-0.0909	-0.0173	0.0006	0.5589	0.4428	2.0571	-7.3142	-0.0353
	(2.9059)	(-0.9603)	(0.4556)	(-0.6298)	(-3.5250)	(2.7294)					

#D-W: Durbin Watson Statistic (at 5% D-W critical values with 100 observations and 4 explanatory variables are 1.592 for lower level and 1.758 for upper level). *AEG: Augmented Eugle-Granger Test for Cointegration (AEG critical value at 5% level of significance is-1.9439). t-statistic in parenthesis. At 5% level of significance, critical value for t-satistic is 1.96

recessionary period, it was 0.8084. Both U_t and V_t for the recessionary period was insignificant and the sign of V_t is negative, which was not expected. Therefore, CRS assumption primarily was holding for the non-recessionary periods.

DISCUSSION

This is the first attempt to estimate a matching function for the US using the JOLTS data. Prior to this study, matching function for the US is estimated by (Blanchard and Diamond, 1989) for the period 1968 to 1981. They have used CPS and the Help Wanted Index data to make their estimations and have found constant returns to scale matching function (Warren, 1996) estimate the matching function for the period April 1969 to December 1973 using the US manufacturing sector data. In the study Warren use a translog matching function for less restrictive econometric specification. The study concludes that the US manufacturing sector have increasing returns to scale matching function. Bleakley and Fuhrer (1997) estimates a matching function for the period 1987-1994 using CPS and Help Wanted Index data. They conclude that the matching function exhibit constant returns to scale. Anderson and Burgess (2000) used a state-level and a state-industry-level panel of accessions, state unemployment and vacancy rates, state-level demographic shares, and various other state- and/or industry-level characteristics by merging data from a variety of sources. These sources include unemployment insurance administrative records, the Current Population Survey (CPS) and assorted published and unpublished data. They find evidence in favor of slightly increasing returns to scale in matching function. Similar studies is done for the U.K. by (Pissarides, 1986) using quarterly data for the period 1967-1983. He finds strong evidence in favor of constant returns to scale matching function. The estimates of Burda and Wyplosz (1994) for some European countries show decreasing returns to scale. With number of estimates for matching function increasing overtime, it is natural that there are estimates for both increasing and decreasing returns to scale matching functions. But such divergences from constant returns to scale are not many in numbers.

This study we estimated matching function for the US using the JOLTS dataset. Though prior studies find strong evidence of constant or increasing returns to scale matching function, but we find evidence of constant or decreasing returns to scale matching function. The nature of returns to scale varies according to business cycle. Economic upswing is associated with constant returns to scale, whereas downswing with decreasing returns to scale. All the prior studies for the

US have used CPS and the Help Wanted Index dataset. Estimation results show that when hirings are estimated using CPS, the matching function shows CRS. This raise concerns about the way data is collected for hirings. It seems that there are discrepancies between estimates based upon JOLTS and the estimates based upon CPS. Further studies need to be done to understand the behaviour of hirings during the recessionary period.

There are couple of concerns, which are worth mentioning here. First, although the CRS assumption holds only for the non-recessionary time period, but theory predicts that returns to scale do not vary with the business cycle fluctuations. Business cycle fluctuations only cause movements along the Beveridge curve. Second, though JOLTS is more suited to estimate a matching function for the US in comparison to other data sources used in previous studies, still the data is limited in terms of showing job-to-job transitions and transitions from unemployment to employment. In the study, attempts are made to adjust hires for the job-to-job transitions, but no adjustments are made to the vacancies and unemployment. To adjust vacancies and unemployment for job-to-job transitions, we need more disaggregated micro level data[10]. Given the growing importance of job-to-job transition (Fallick and Fleischman, 2001; Nagypal, 2005), any further studies to estimate matching function need to account for the job-to-job transitions more rigorously.

CONCLUSION

This is the first attempt to estimate a matching function for the US using newly created JOLTS dataset of the US Department of Labour. JOLTS is the only existing data source to measure vacancies, hires and separations at the establishment level at a regular monthly frequency in the US This makes it an ideal data source to estimate matching function for the US The study does not find stable constant returns to scale matching function for the period 2000 - 2009. Rather the functional form of the matching function is found to be time varying according to business cycles. A standard close to constant returns to scale matching function is only obtained for the non-recessionary time periods. During recession, the matching function exhibited decreasing returns to scale. Given that the nature of matching function may vary overtime, it is important to take into account the effects of business cycle fluctuations on the behaviour of matching function in order to understand the labour and job flows in an economy.

REFERENCES

Adam, A.M., 2011. Financial openness induced growth and poverty reduction. Int. J. Applied Econ. Finan., 5: 75-86.

Anderson, M.P. and S.M. Burgess, 2000. Empirical matching functions: Estimation and interpretation using state-level data. Rev. Econ. Stat., 82: 93-102.

Berman, E., 1997. Help wanted, job needed: Estimates of a matching function from employment service data. J. Lab. Econ., 15: 251-291.

Blanchard, O.J. and P. Diamond, 1989. The beveridge curve. Brookings Paper on Economics. http://www.jstor.org/pss/2534495

Bleakley, H. and J.C. Fuhrer, 1997. Shifts in the beveridge curve, job matching and labor market dynamics. New England Econ. Rev., 9: 65-89.

[10]Recently BLS has started releasing information on micro level labor market dynamics. But still these micro level data are not yet publicly available

Burda, M.C. and C. Wyplosz, 1994. Gross worker and job flows in Europe. Eur. Econ. Rev., 38: 1287-1315.

Diamond, P.A., 1982. Aggregate demand management in search equilibrium. J. Political Econ., 90: 881-894.

Dickey, D.A. and W.A. Fuller, 1981. The likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49: 1057-1072.

Engle, R.F. and C.W.J. Granger, 1987. Co-integration and error-correction: Representation, estimation and testing. Econometrica, 55: 251-276.

Faberman, J., 2005. Studying the labor market with the job openings and labor turnover survey. BLS Working Paper. http://ideas.repec.org/p/bls/wpaper/ec050140.html

Fallick, B. and C. Fleischman, 2001. The importance of employer-to-employer flows in the U.S. labor market. Federal Reserve Bank Board of Governors, http://ideas.repec.org/p/fip/fedgfe/2001-18.html.

Feve, P. and F. Langot, 1996. Unemployment and the business cycle in a small open economy: G.M.M. estimation and testing with french data. J. Econ. Dyn. Control, 20: 1609-1639.

Lohano, H.D. and F.M. Soomro, 2006. Unit root test and forecast of milk production in Pakistan. Int. J. Dairy Sci., 1: 63-69.

Mumford, K. and P.N. Smith, 1999. The hiring function reconsidered: On closing the circle. Oxford Bull. Econ. Statistics, 61: 343-364.

Nagypal, E., 2005. Job-to-Job Transitions and Labour Market Fluctuations. Northwestern University, Kellogg, Logo.

Ong, H.B., and S.H. Muzafar, 2008. Evidence of ongoing convergence within ASEAN. J. Applied Sci., 8: 2592-2598.

Petrongolo, B. and C.A. Pissarides, 2001. Looking into the black box: A survey of the matching function. J. Econ. Literature, 39: 390-431.

Pissarides, C.A., 1986. Unemployment and vacancies in Britain. Econ. Rev., 75: 676-690.

Pissarides, C.A., 2000. Equilibrium Unemployment Theory. 2nd Edn., MIT Press, Hayward Street Cambridge, MA.

Rogerson, R., R. Shimer and R. Wright, 2005. Search-theoretic models of the labor market: A survey. J. Econ. Literature, 43: 959-988.

Sahin, A., Y. Akdi and F. Arslan, 2007. Wheat yield dynamics: A structural econometric analysis. Pak. J. Biol. Sci., 10: 3533-3540.

Shimer, R., 2005. The cyclical behavior of equilibrium unemployment and vacancies. Am. Econ. Rev., 95: 25-49.

Stewart, J., 2002. Recent trends in job stability and job security: Evidence from the March CPS. U.S. Bureau of Labor Statistics. http://www.bls.gov/osmr/abstract/ec/ec020050.htm

Van-Ours, J., 1991. The efficiency of the dutch labor market in matching unemployment and vacancies. De Economist, 139: 358-378.

Warren, R.S., 1996. Returns to scale in a matching model of the labor market. Econ. Lett., 50: 135-142.

Yashiv, E., 2000. The determinants of equilibrium unemployment. Am. Econ. Rev., 90: 1297-1322.