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Trade Liberalization and Aggregate Matching Function in India

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Abstract

This article investigates the link between trade liberalization and the job matching process in India. The aggregate matching function in India is estimated by incorporating the trade openness as a proxy for trade liberalization. The monthly data are drawn from Employment Exchange in India, the only public employment service in the country. Overall, it appears that trade liberalization leads to a decline in new hires. However, the analysis of period decomposition shows that correlation between trade-to-GDP ratio and new hires is negative and significant only in the period of the Ninth Plan, 1997 to 2002, when political influence delayed economic reform. The suggestion is made that the negative relationship between trade liberalization and new job creation does not hold except for the period of political influence and thus the Indian government should continue to promote external reform.

JEL Classification: F14, F16, J60, O53

Keywords: Matching Function, Trade Liberalization, Labor Market, India

* This paper is a revised and updated version of Ch. 5 in my joint monograph (Lee, Song, Cho, and Choi), "Changes in the Labor Market since India's Economic Reforms" (2013).

Contents

1. Introduction

Before the early 1990s, the Indian economy was relatively closed. Average tariff rates were more than 80%, proportion of tradable goods protected by quantitative restrictions was higher than 90%, and FDI was strictly limited (Alessandrini et al. 2011). In late 1991, India accepted the IMF bailout program to overcome its balance of payment crisis, which set off unexpected trade reforms. As a result, India's trade openness has more than been trebled since the economic reform of 1991 (see Figure 3).

Many scholars have extensively studied effects of trade liberalization on economic outcomes in India. When focusing on the labor market, various topics have also been investigated such as the relationship between trade liberalization and employment (Sahoo 2010; Mitra 2009; Banga 2009; Goldar and Aggarwal 2012), employment structure (Goldar and Aggarwa 2010; Srinivasan 2010); unemployment (Hasan et al. 2012), income (Hasan, Mitra and Ramaswamy 2007; Topalova 2007), income inequality (Dutt 2005; Kumar and Mishra 2008), labor demand (Berman, Somanathan and Tan 2005; Chamarbagwala 2006; Sahoo 2010) or labor demand elasticity (Hasan, Mitra and Ramaswamy 2007), poverty (Hasan, Mitra and Ural 2007; Topalova 2007; Panda and Ganesh-Kumar 2009; Mehta and Hasan 2012), wage (Dutt 2003; Chamarbagwala 2006; Banga 2005), and so on.

The aim of this paper is to examine the link between trade liberalization and the state of the labor market, more specifically the job matching process in India. This paper adopts the aggregate matching function to represent the job matching process. The inputs of the matching function are volumes of job-seekers and vacancies and the output is new job hires. The matching function is a simple but the most representative of all methods for showing labor market frictions in an economic model, and explaining why unemployment and vacant jobs coexist. It is one of the most important elements in search-matching models and has been widely used in macroeconomics and labor economics. To the best of my knowledge, the matching function of the Indian labor market has not been estimated. The research most closely-related to this paper may be Hasan et al. (2012), which investigate the effect of trade liberalization on unemployment. The indirect link between this paper and Hasan et at. (2012) is the negative relationship between new hires and unemployment.[1]

The data are drawn from various publications of "*Employment Exchange Statistics*" published by the Directorate General of Employment and Training (DGE&T) in the Ministry of Labour and Employment in India. DGE&T gathers data from almost 1,000 public employment agencies, which

[1] Most international trade models such as Ricardian, Heckcher-Ohlin, and even Melitz-type assume perfect competition, which does not allow unemployment in a model. In recent literature (for example Felbermayr, Prat and Schmerer 2011), economic models incorporating labor market rigidity have been introduced to explore the link between trade liberalization, either opening an economy or reducing/eliminating tariffs, and unemployment. To the best of my knowledge, in all model, the channel that trade liberalization changes the value of marginal product of labor leads to an increase or decrease in new hires, employment, and unemployment. Since overall effect relies on the share of sectors having comparative advantage with higher value of marginal product of labor, the effect of trade liberalization on job matching process and thus unemployment is an empirical question. For more detailed information, please see Dutt, Mitra and Ranjan (2009).

is called “Employment Exchange in India”, across states. The frequency of the data used in this paper is monthly and covers the period from April 1990 to March 2012.

With the data from Indian Employment Exchange, the aggregate matching functions are estimated by incorporating trade openness. The trade openness, the sum of imports and exports divided by total GDP, is adopted as a proxy for trade liberalization. In addition, different degree of trade liberalization over time is considered. Goldberg et al. (2010) argue that the degree of trade liberalization in India differs between the period of the Eighth Plan (1992-1997) and the period of the Ninth Plan (1997-2002) in that the Eighth Plan period represents a time of progressive economic reform, while the Ninth Plan period was a time in which economic reform was delayed by political interference. Thus, the period is divided into 5 sub-periods: (1) before economic reform (until 1991), (2) progressive economic reform (1992 to 1997), (3) delayed economic reform (1998 to 2002), (4) economic boom (2003 to 2008), and (5) post global financial crisis (since 2009). The aggregate matching functions with trade openness are estimated for each period to examine whether or not the degree of trade liberalization is different over time.

The results from empirical matching functions show that on average there is a negative correlation between trade openness and new job hires, which implies a positive relationship between trade liberalization and unemployment. This finding seems to accord with a widely held public view that trade liberalization increases unemployment, but it differs from Hasan et al. (2012) showing that overall, there is no link between trade liberalization and unemployment. Furthermore, the finding contradicts Dutt, Mitra, and Ranjan (2009) arguing that unemployment and trade openness are negatively related in cross-country analysis.

However, the empirical matching functions in each sub-period show that there is no correlation between trade liberalization and new hires except for the period of delayed economic reform (1998 to 2002) when domestic sectors’ performance in previous years was reflected in economic reform. This result implies that delayed trade reform to protect domestic firms and industries could lead to a reduction in new hires, and thus an increase in unemployment. Therefore, it is recommended that the Indian government continue to promote external reform because trade liberalization is not harmful to the Indian labor market.

This paper is organized as follows. Section 2 introduces a brief overview of the matching function. Section 3 presents empirical strategies including empirical model, data, and econometric issues. Section 4 reports the results of matching function estimations and Section 5 concludes the paper.

2. A Brief Overview of the Matching Function

The job matching process is characterized by trading friction, incomplete information, and heterogeneities between job-seekers and firms. The matching function summarizes the job matching process and plays a key role in describing the labor market dynamics and efficiencies in search-matching models. Matching function relates the joint movement of job-seekers and vacancies to new hires and is generally given by $H = m\,(S, V)$, where H denotes the number of new hires in a given interval, S the stock of job-seekers, V the stock of vacant jobs. Variables can be time-series, cross-section, or both dimensions.[2]

The following properties are natural and testable assumptions of the matching function: $\frac{\partial m}{\partial S} > 0, \frac{\partial m}{\partial V} > 0$; $m(0, V) = m(U, 0) = 0$; and $m_{SS} < 0, m_{VV} < 0$, which indicate that new hires increase with respect to both arguments, at least one job-seeker and one vacancy are required to generate a new hire, and the matching function is concave with respect to both arguments. Furthermore, for a stable and unique equilibrium of the unemployment, matching functions are assumed to be constant returns to scale in search-matching models (Pissarides 2000, p. 6).

This paper employs a specification of the matching function shown in Equation (1).

$$(1) \qquad H_t = M_t(S_t, V_t) = A_t S_t^{\alpha} V_t^{\beta} \text{ where } A_t = A \cdot exp(\delta t + \varepsilon_t)$$

It is a Cobb-Douglas specification and is a standard in empirical matching literature (Petrongolo and Pissarides 2001). Other functional forms can also be adopted such as translog or CES (constant elasticity of substitution) but empirical evidence supports the Cobb-Douglas specification (Pissarides 2000, page 6). All the variables are indexed by t because the data used in this paper are monthly time-series data. Taking logs, Equation (1) is transformed to be linear in parameters in Equation (2).

$$(2) \qquad ln\, H_t = c + \alpha\, ln\, S_t + \beta\, ln\, V_t + \delta T + \varepsilon_t \qquad \text{where } \ln A = c$$

The α is referred to as the elasticity of the matching function with respect to job-seekers and β is the elasticity with respect to job vacancies. Loosely speaking, α is the percentage change in H with respect to one percent increase in S. T is time trend and its coefficient δ can often be interpreted as additional effects in the efficiency of the matching process over time.

[2] In general, time series is used for economy-wide aggregate matching functions, and panel structure is applicable for industry-time or region-time disaggregated matching functions.

The degree of returns to scale for the matching function is obtained by the sum of α and β and can be tested under the null hypothesis: $\alpha + \beta = 1$ in (1) or (2). The α and β are also considered as relative importance (a contribution of matching) of job-seekers and vacancies in the job matching process. In addition, these parameters are often interpreted as the matching shares of job-seekers and vacancies in creating new job matches. For example, the matching function with a small α and large β implies a relative shortage of labor demand, which indicates that an additional vacant job leads to a new hire with a high probability, while an additional job-seeker has almost no contribution to new hires (Fahr and Sunde 2004, p. 411). In this situation, government policies to promote labor demand are recommended for new job creation.

Matching function has been extensively studied in the macro-labor literature. Generally there are two approaches: economy-wide aggregate matching functions with time-series data and disaggregated matching functions across regions and industry with panel data. Petrongolo and Pissarides (2001) provide an extensive survey on empirical matching functions. Since then, there have still been a considerable number of studies on matching functions with various objectives over countries: matching function itself; functional forms, the degree of returns to scale, data issues of matching function variables, matching efficiencies across industries or regions and other subjects.

Since this paper estimates the aggregate matching function for India, recent articles are briefly introduced regarding aggregate matching functions and matching functions in Asian countries. Poeschel (2012) examines negative time trend in empirical matching function with the U.S. labor market data and argues that deteriorating matching efficiency, represented by negative time trend of a matching function, could be a statistical illusion due to omitted variable bias. Borowczyk-Martins et al. (2013) estimates aggregate matching function for the U.S. economy with 21st century data. They suggest an estimation method to correct the bias of existing estimates of matching elasticities. They also propose that the elasticity for vacancies is 0.7 in the U.S. with the data from 2001 to 2011. Kohlbrecher et al. (2013) provide the estimates for matching function elasticities with German administrative data and show the importance in controlling various heterogeneities even in the aggregate matching function. They also find the relevance of Cobb-Douglas specification of the matching function by comparing the data generated from a labor selection model.

Liu (2011) estimates matching functions for three different groups of job-seekers in China: unemployed, on-the-job search, and migrant job-seekers from rural to urban areas. Liu's main finding is that congesting effects from other groups are significant, especially the effect of on-the-job search on the unemployed. Kanik et al. (2013) analyze the aggregate matching function in Turkey, using the data between January 2005 and February 2013. Regarding the matching function, the estimates show a positive relationship between job finding rate for workers and labor market tightness, the ratio of vacancies to job-seekers, are consistent with the rest of the literature. Kano and Ohta (2004) and Kano and Ohta (2005) investigate matching functions in the Japanese labor market. Kano and Ohta (2004) focus on the long-run relationship among the main variables in the matching function and find that these variables are cointegrated and conventional within estimates in panel regression are significantly biased. Kano and Ohta (2005)'s main finding is that more urbanized regions reveal lower matching efficiencies, which implies that the matching efficiency is negatively related to population density and per capita income. Choi (2007) estimates matching functions in

Korea and shows that constant returns to scale of the matching function is relevant to the Korean labor market.

Earlier studies focused on estimating matching function parameters and the degree of returns to scale of the matching function in European countries and the United States. Recent works tend to investigate particular issues as well as estimation of matching function itself, shown above. Moreover, empirical matching function and its application are performed not only for advanced nations but also for emerging markets such as China (for example, Liu 2011). It is expected that this paper also adds some contribution to recent matching function literature. To the best of our knowledge, it is the first original work to estimate the aggregate matching function in India.

3. Empirical Strategies

3.1. Specification of a Matching Function with Trade Liberalization

This paper examines the link between trade liberalization and the job matching process in India. There are many measures related to trade liberalization such as tariffs, import quotas, antidumping duties, export duties, and so forth. Choosing a single measure of trade liberalization is almost impossible. This paper employs trade openness as a proxy for trade liberalization because the data for the matching function are monthly and monthly data for openness can be easily collected.[3] Trade openness is the ratio of the sum of exports and imports to total GDP ($\frac{Exports+Imports}{GDP}$). It incorporates the effects of many different policies regarding trade liberalization as well as non-trade related policies such as macroeconomic shocks and policies, geographical attributes, and other factors (Dutt, Mitra and Ranjan 2009, p. 38). To incorporate trade openness in the matching function, A_t in Equation (1) is modified to $A \cdot exp(\delta T + ln\, openness\ + \varepsilon_t)$ and econometric model for estimation is revised as follows:

$$(3) \qquad ln\, H_t = c + \alpha\, ln\, S_t + \beta\, ln\, V_t + \delta T + \mu\, ln\, Openness + \varepsilon_t$$

where ln *A* equals *c* and *ln Openness* is the natural logarithm of trade openness.

3.2. Data Description

The data for matching function variables are drawn from Employment Exchange in India. Three key variables for matching functions are the numbers of new hires, job-seekers, and vacancies. The data are collected from various annual publications of “Employment Exchange Statistics” published by the Directorate General of Employment and Training (henceforth referred to as DGE&T) in the

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[3] Another candidate is the important penetration rate, $\frac{imports}{GDP}$ or $\frac{imports}{GDP-exports+imports}$. This paper also used these two measures for estimation but there is no significant difference from the estimation using openness. Moreover, both variables did not pass stationarity tests. Therefore, analysis with import penetration rate in not reported in this paper.

Ministry of Labour and Employment in India. DGE&T collects the data from local public employment agencies, which is called "Employment Exchange in India".

Employment Exchange in India (henceforth referred to as EEI) is the only public employment service that helps job-seekers across India (DGE&T 2012). EEI covers 28 states and 7 union territories with 966 offices and provides not only job matching service between job-seekers and business but also vocational guidance, carrier counseling, and labor market information gathering such as data collection for employment and unemployment (DGE&T 2012, p. 1). The data from EEI include entire areas, occupations, and industries in India. These data are also used to estimate the state-level unemployment rates in India, which demonstrates the data's usability and reliability.

The data used in this paper are time-series with a frequency of one month. The range covered by the data is from April 1990 to March 2012 and hence the total observation is 264. Although more informative state-level data are available, time-series aggregate data are utilized because the data in the 1990s are not available at a state level but at aggregate time-series level. The 1990s is the period of progressive economic reform, which implies the most important period in this paper.

This paper uses the data for "Registrations", Vacancy notified", and "Placements" in Employment Exchange Statistics. These variables correspond to job-seekers, vacancies, and new hires in the matching function. Trade openness is constructed by using the data from UN Comtrade and CEIC Databases. Descriptive statistics of the variables in the matching function as well as trade openness are illustrated in Table 1.

Figure 1 illustrates annual trends of the number of job-seekers, both flow and stock values. The "s" here represents stock value at the end of each year and "f" denotes flow value in a given period between January 1 and December 31 in a year. Stock value of job-seekers increased from approximately 30 million in 1988 to 40 million in 2011, which implies 1.4 percent of annual growth during this period. Annual growth rate of the stock value was about 3.1 percent between 1988 and 2001, and was almost 7 percent before economic reforms, that is until 1991, which implies a sharp increase in unemployment before economic reform. It showed a declining trend since 2001, with the exception of 2006, with 5.3 percent growth. However, it has shown an upward trend since 2008, showing an increase in unemployment.

Flow value of job-seekers can be considered as annual inflow of job-seekers. Annual average of persons who were in "job search" between 1988 and 2011 was 5.8 million. Except 2006, where the number of job-seekers was 7.3 million, new inflow of job-seekers each year was 6 to 7 million. In particular, the flow value shows an increasing trend and this also indicates an increase in unemployment since the Great Recession starting from 2008.

Figure 2 presents flow values of job-seekers, vacancies, and new hires. Vacancies and new hires show co-movement over time. The numbers of vacancies and new hires tended to decline until 2003 but these measures began to increase from 2003, and it should be noted that these two values increased sharply in 2010 and 2011. The co-movement of vacancies and new hires reveals the importance of vacancies on new hires.

Figure 3 illustrates the trend of trade openness in the 1990s and the 2000s. It shows an upward trend, especially a sharp increase from 2003 when the Indian economy started booming. India's trade volume was approximately 0.15 as a proportion of GDP in 1990, increased substantially up to 0.52 in the middle of 2008, plummeted to 0.35 in 2009, but finally recovered to over 0.5 in 2012.

3.3. Econometric Issues

As shown in Equation (3), this paper's estimation is involved in time-series analysis. Thus, before performing time-series estimation, stationarity of each variable is tested and the results are presented in Table 2. All variables are in natural logarithm form following the regression specification in Equation (3) and are seasonally adjusted.[4] The results of augmented Dickey-Fuller Test indicate that all variables are either stationary with drift or with trend: *ln H, ln S, and ln V* are stationary, while *ln Openness* is trend-stationary.

In the regression analysis, the dependent and independent variables are flow variables. In estimation of production function or matching function, theoretically dependent variable is flow and explanatory variables are stock values, which causes an endogeneity problem. For example, in Equation (3), H_{2011} is the number of new hires in 2011, while S_{2011} and V_{2011} are cumulative values at the end of 2011, which is December 31 2011. In this case, the depletion of *H* in a year leads to decreases in *S* and *V*, which causes endogeneity problem due to reverse causality. Thus, generally lagged values of *S* and *V* are used for instrumental variables. However, instrumental variables are not used in this study because flow values of *S* and *V* are used instead of stock values. In regression, what is important is how variations of *S* and *V* explain variation of *H*. Changes in stock values of *S* and *V* are determined by flow values of *S* and *V* and thus flow values can possibly be proxy variables for stocks of *S* and *V*. More importantly, stock values of job vacancies are not available, thus using flow values of job-seekers and vacancies are inevitable.

Estimation methods in the regression analysis are OLS with Newey-West standard error, autoregressive (AR) model, and feasible generalized least square (FGLS).[5] These methods are used to correct serial correlation of disturbances, which can cause biased estimates. In addition, first lag of the dependent variable is controlled to correct serial correlation.[6] Another way to correct serial correlation is the differencing method but it may give rise to a problem when the estimates are

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[4] In this paper, all time-series data are seasonally adjusted. Seasonality is a component of time series data and it occurs in the same magnitude during the same period of time each year. The presence of seasonality may mask other important characteristics of the data such as the cyclical behavior of an economic trend. For example, the U.S. Bureau of Labor Statistics provides seasonally adjusted economic time series such as price indices and unemployment statistics. Seasonal adjustment is the process of removing seasonal factors from a time series in order to reveal non-seasonal characteristics of a series. This paper uses X-12-ARIMA as a method of seasonal adjustment. X-12-ARIMA is a method of seasonal adjustment produced and maintained by the U.S. Census Bureau. It is used for all official seasonal adjustments at the U. S. Census Bureau (http://www.census.gov/srd/www/x12a/).

[5] Newey-West estimator provides consistent standard errors in the presence of serial correlation. AR estimator assumes autoregressive disturbance and correct it for unbiased estimates. FGLS corrects 1st order serial correlation of disturbance. This paper adopts Prais-Winsten regression with Cochrane-Orcutt procedure. Prais-Winsten uses feasible generalized least square (FGLS) method to estimate coefficients in the linear model where errors are autocorrelated (Greene 2003, pp. 273-276). This paper employs Prais-Winsten transformation not to lose observation and Cochrane-Orcutt iterative procedure for estimation efficiency in estimating serial correlation coefficient of disturbances.

[6] Controlling the first lag is equivalent to controlling all the lags of independent variables, and hence in case, the coefficients of the matching function can be interpreted as current period or short-run impacts of job-seekers and vacancies on new job hires.

interpreted. More importantly, differencing is applicable only if disturbance's coefficient (ρ in $\varepsilon_t = \rho\varepsilon_t + u_t$) is exactly 1. In this paper, coefficients of serial correlation are about 0.1 in all cases and thus differencing is not applied.

Trade liberalization is also exposed to the problem of endogeneity. In recession, new hires may decrease and as a result, unemployment increases. In this situation, the government can change its external policy toward protectionism and this can cause a decrease in trade openness, which is endogeineity due to reverse causality. To address this, lagged values of openness are used as instruments.

Regarding trade liberalization in India, it is important to notice that the degree of the reforms may vary over different periods of time. Topalova and Khandelwal (2011) show the evidence that the Indian government performed further trade liberalization during the period of the Eighth Plan (1992-1997), but after the turnover of political power in the 1997 election, trade liberalization under the Ninth Plan (1997-2002) was changed to reflect firm and industry performance in previous years. Based on this evidence, Goldberg et al. (2010) suggest that after 1997, trade liberalization was subject to political influence.

To incorporate different degrees of trade liberalization over time in the regression analysis, the period is divided into 5 sub-periods: (1) the period before economic reform (before 1992) (2) the period of economic reform driven by external factors after the 1991 reform (from 1992 to 1997); (3) the period of economic reform that reflected strong requests from domestic firms' and industries' (from 1998 to 2002); (4) the period of economic boom (from 2003 to 2008); and (5) the period after the global financial crisis (after 2009).

4. Results

This section presents empirical matching functions including trade openness. The results from all observations from April 1990 to March 2012 are illustrated and the findings are displayed with each period defined in the previous section. The key interest is the relationship between openness and new job hires in the matching function.

Table 4 shows the results by OLS with the Newey-West estimator and 2SLS.[7] Column [1] presents the estimated coefficients in Equation (3) without *ln Openness*. Column [2] presents the estimated coefficients with *ln Openness*. Column [3] presents the results with an instrument for *ln Openness*, the first lag of its value. Column [4] presents the results by 2SLS.[8]

In all estimations, the elasticity of matching function with respect to vacancies is much higher than the elasticity for job-seekers. The estimates for vacancies range from 0.77 to 0.83 and are statistically significant, while the estimates for job-seekers are approximately 0.10 but not statistically significant. This result confirms the strong co-movement of vacancies and new hires in

[7] Various lagged values of ln Openness are used for instruments and the 1st and 2nd lags are selected.
[8] In this paper, validity of instrument in 2SLS estimation in all cases is confirmed by statistical significance in the first stage regressions. About over-identifying restrictions, Sargan's Chi-squared test and Sargan statistic and Wooldridge's (1995) robust score test indicate that instruments may be valid.

Figure 2, which implies shortage of labor demand where additional vacancy leads to a new hire with a high probability but an additional job-seeker creates almost no new hires.

With and without instruments, the effect of trade openness is negative and statistically significant, as shown in columns [2], [3], and [4] in Table 4. This finding indicates that new hires in the employment service decline as the degree of trade openness increases. It implies a negative effect of trade liberalization on new job creation in India, which also shows a negative impact on unemployment. This negative correlation between trade liberalization and new hires as well as vacancy-dependent job matching process in India does not change after serial correlation is corrected by different specifications of the regression model including the first lag of the dependent variable (see Table 5) and different estimation methods, FGLS and AR model (see Tables 6 and 7). The result may be consistent with a widely held public view that trade liberalization increases unemployment. But the finding contradicts the previous studies: Dutt et al. (2009) and Hasan et al. (2012). Dutt et al. find that a strong and robust negative relationship exists between trade openness and unemployment in cross-country analysis. Hasan et al. focusing on India show that on average there is no correlation between tariff reductions and unemployment.

However, in the analysis of the 5 sub-periods defined in this paper, the findings show that trade liberalization and new job hires are negatively related only in period 3 (January 1998 to December 2002) when domestic firm and industry performance in previous years was reflected in economic reforms. The negative effect of trade openness on new hires is significant only in period 3 and it is not statistically significant in other periods (see the bolded rows in Tables 8 and 9). This result implies that a gradual liberalization to protect domestic sectors could actually cause a decline in new job hires, and in turn, an increase in unemployment. It also implies that unless trade liberalization is progressive, its impact is limited in the job matching process. Therefore, it is suggested that trade liberalization is not harmful to the Indian labor market because the effect of openness on new job hires, and hence unemployment, is limited in India. The evidence also recommends that the Indian government continue to promote external economic liberalization.

5. Conclusion

In this paper, the relationship between trade liberalization and the job matching process is empirically examined using the data from Employment Exchange in India, the only public employment service in the country. It is found that the job matching process in India is vacancy-dependent, meaning that job vacancies' contribution to creation of new hires is much larger than job-seekers' importance. The key result shows that the link between trade liberalization and the job matching process in India is negatively associated only in the period of delayed economic reform. Although overall effect is negative, the analysis of period decomposition supports no relationship between trade liberalization and new job hires except the period of political influence.

To my best knowledge, it is the first original work to estimate aggregate matching functions in India. Since it represents the first step into exploring empirical matching functions for India, there may be various issues to be addressed. To develop better picture of the job matching process in India and its applications, representativeness of the data generated by Employment Exchange must be fully examined. Utilization of more disaggregated data like state-level information must also be realized in order to conduct analysis for a more general and accurate state of the Indian labor market.

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Data Sources

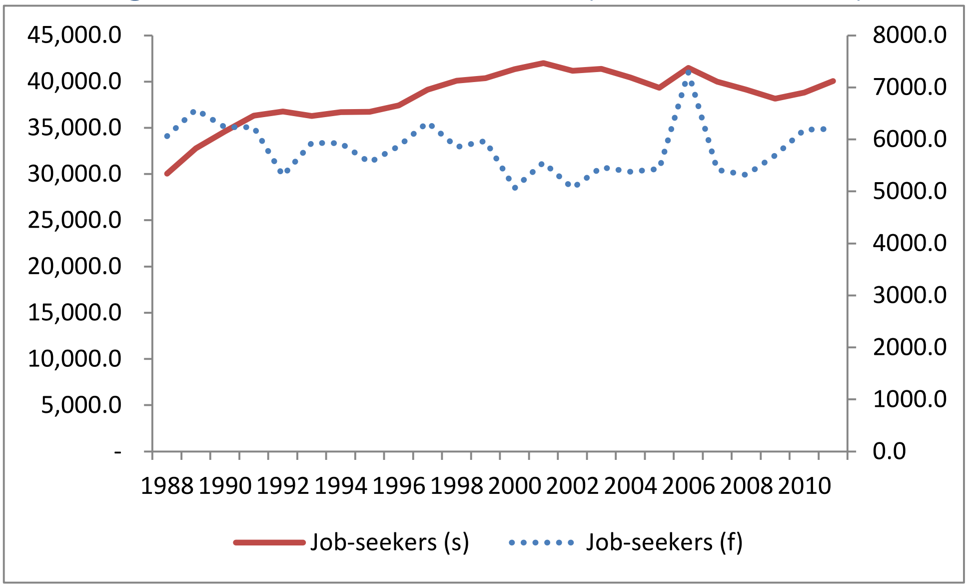
CEIC Database http://www.ceicdata.com
UN Comtrade Database http://comtrade.un.org/db/default.aspx

Internet Sources

http://www.census.gov/srd/www/x12a.

Figures

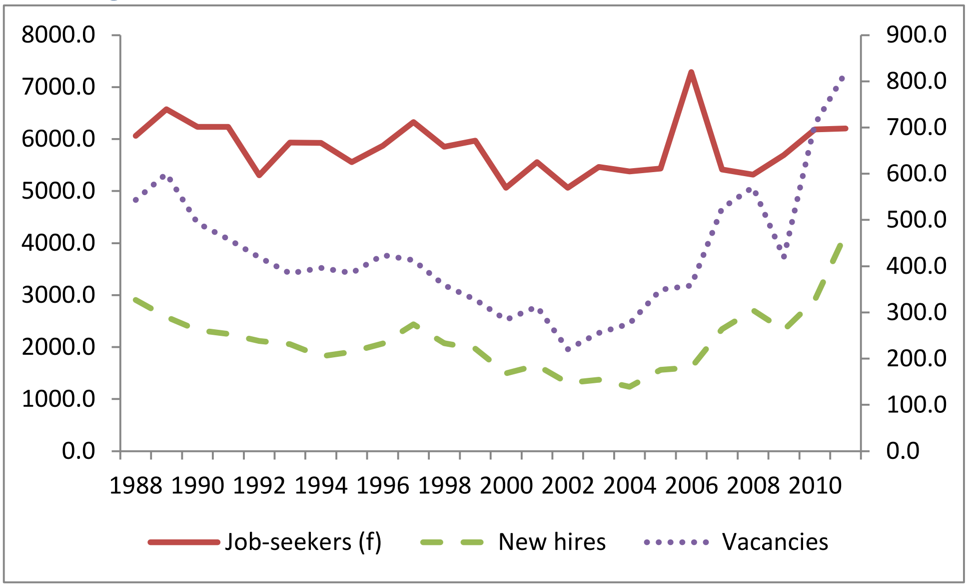
Figure 1: Annual Trends of Job-seekers (flow and stock values)



Source: various issues of "Employment Exchange Statistics."
Notes:

1) Unit is thousand. (s) represents stock value and (f) stands for flow value.
2) Job-seeker (s) uses the left axis and job-seeker (f) the right axis.
3) The period is from 1988 to 2011.
4) The data are seasonally adjusted.

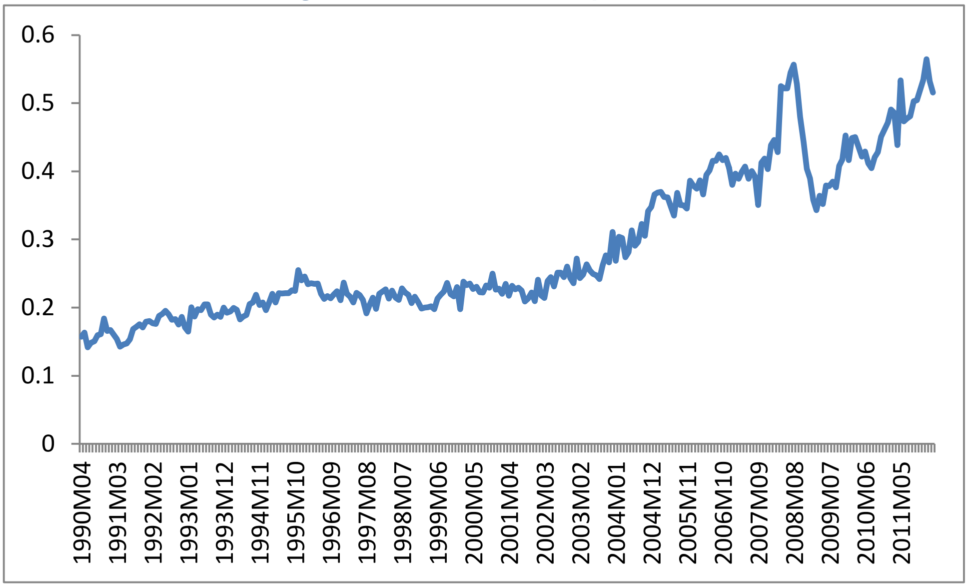
Figure 2: Annual Trends of Job-seekers, Vacancies, and New Hires



Source: various issues of "Employment Exchange Statistics."
Notes:

1) Unit is thousand. All measures are flow values.
2) The period is from 1988 to 2011.
3) The data are seasonally adjusted.

Figure 3: Trend of Trade Openness



Source: UN Comtrade and CEIC database

Note:

1) The series is seasonally adjusted.
2) $\text{Trade Openness} = \frac{Exports+Imports}{GDP}$
3) The data ranges from April 1990 to March 2012.

Tables

Table 1: Summary Statistics of the variables

Variable	Obs	Mean	Std. Dev.	Min	Max
H	264	19.68	8.79	3.9	71.9
S	264	486.96	189.71	191	1654
V	264	35.12	16.55	10.6	143.7
Openness	264	0.29	0.11	0.13	0.58

Note:

1) Unit of H, S, V are thousand.
2) All variables' time frequency is month.
3) $\text{Openness} = \frac{\text{Exports+Imports}}{\text{GDP}}$.

Table 2: Unit Root Test of the variables

Series	Augmented Dickey-Fuller Test Statistic	
	drift	drift and trend
$ln\ H_t$	-8.157***	-8.142***
$ln\ V_t$	-6.101***	-6.076***
$ln\ S_t$	-10.712***	-10.769***
$ln\ Openness_t$	-1.178	-4.207***

Notes:

1) H is the number of new hires, V job vacancies, S job-seekers, Openness the ratio of the sum of exports and imports to GDP, and IPR (Import Penetration Rate) imports divided by GDP.
2) All series are in natural log.
3) Augmented Dickey-Fuller Tests are performed for stationarity with no lagged difference.
4) The null hypothesis for augmented Dickey-Fuller test is a unit root of the series.
5) The Augmented Dickey-Fuller test examines whether a time series follows a unit root process. In the Augmented Dickey-Fuller test, one can also include differences of lagged values.
6) The data covers from April 1990 to March 2012 (total observation is 264)
7) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 3: Division of the Period

term	
Period 1	Before economic reform (until Dec. 1991)
Period 2	Economic reform by external factors after the 1991 reform (Jan. 1992 – Dec. 1997)
Period 3	Economic reform that reflected domestic demand of various firms and industries (Jan. 1998 – Dec. 2002)
Period 4	Economic boom (Jan. 2003 – Dec. 2008)
Period 5	After the global financial crisis (after Jan. 2009)

Table 4: Results by OLS with Newey-West standard error

variables	[1] basic	[2] with openness	[3] with IV	[4] 2SLS
constant	-0.345	-1.257*	-1.054	-1.247*
	(0.453)	(0.666)	(0.641)	(0.735)
ln S	0.099	0.098	0.093	0.094
	(0.073)	(0.073)	(0.073)	(0.074)
ln V	0.767***	0.828***	0.815***	0.829***
	(0.052)	(0.061)	(0.062)	(0.065)
ln Openness		-0.349**		-0.354**
		(0.136)		(0.172)
L.ln Openness			-0.285**	
			(0.139)	
trend	0.000	0.001	0.001*	0.001*
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	264	264	263	262
R^2	0.674	0.684	0.681	0.683
DW statistic	1.790	1.880	1.867	yes
Serial correlation (p-value)	0.089	0.335	0.286	no

Note:

1) The dependent variable is the natural log of the number of new hires.
2) The last row presents p-values of Durbin's alternative test for serial correlation. Its null hypothesis is no serial correlation. Rejecting the null indicates serial correlation of disturbances.
3) The first and second lags of ln Openness are used for instruments.
4) The data ranges from April 1990 to March 2012.
5) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 5: Results by OLS with the first lag of the dependent variable and Newey-West standard error

variables	[1] basic	[2] with openness	[3] with IV	[4] 2SLS
constant	-0.467	-1.400*	-1.221*	-1.409*
	(0.483)	(0.728)	(0.706)	(0.805)
ln M(-1)	0.115	0.118	0.121	0.119
	(0.080)	(0.079)	(0.079)	(0.078)
ln S	0.104	0.103	0.098	0.099
	(0.075)	(0.075)	(0.075)	(0.075)
ln V	0.697***	0.757***	0.743***	0.759***
	(0.064)	(0.069)	(0.071)	(0.073)
ln Openness		-0.356**		-0.369**
		(0.140)		(0.180)
L.ln Openness			-0.301**	
			(0.145)	
trend	0.000	0.001**	0.001*	0.001*
	(0.000)	(0.001)	(0.001)	(0.001)
Observations	263	263	263	262
R^2	0.682	0.693	0.690	0.692
DW statistic	2.075	2.162	2.162	
Serial correlation (p-value)	0.374	0.065	0.063	

Note:

1) The dependent variable is the natural log of the number of new hires.
2) The last row presents p-values of Durbin's alternative test for serial correlation. Its null hypothesis is no serial correlation. Rejecting the null indicates serial correlation of disturbances.
3) The data ranges from April 1990 to March 2012.
4) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 6: Results by FGLS

variables	[1] basic	[2] with openness	[3] with IV
constant	-0.238	-1.144**	-0.889*
	(0.382)	(0.497)	(0.487)
ln S	0.084	0.089	0.079
	(0.067)	(0.066)	(0.067)
ln V	0.762***	0.821***	0.805***
	(0.040)	(0.044)	(0.044)
ln Openness		-0.332***	
		(0.126)	
L.ln Openness			-0.260**
			(0.124)
trend	0.000	0.001**	0.001*
	(0.000)	(0.001)	(0.001)
Observations	263	263	262
Adjusted R^2	0.633	0.657	0.649
Rho	0.107	0.063	0.072
DW d-stat (original)	1.790	1.880	1.867
DW d-stat (transformed)	2.032	2.012	2.019

Note:

1) The dependent variable is the natural log of the number of new hires.
2) FGLS uses Prais-Winsten transformation and Cochrane-Orcutt Iterative Procedure.
3) The data ranges from April 1990 to March 2012.
4) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 7: Results by AR model

variables	[1] basic	[2] with openness	[3] with IV
constant	-0.047	-0.898**	-0.752*
	(0.312)	(0.429)	(0.394)
ln S	0.077	0.098	0.088
	(0.060)	(0.065)	(0.066)
ln V	0.725***	0.773***	0.764***
	(0.035)	(0.041)	(0.039)
ln Openness		-0.261*	
		(0.137)	
L.ln Openness			-0.235**
			(0.112)
trend	0.000	0.001	0.001
	(0.000)	(0.001)	(0.001)
Observations	264	264	263
Autoregressive disturbance			
L1	0.114**	0.068	0.073
	(0.049)	(0.055)	(0.055)
L2	0.199***	0.162**	0.173***
	(0.059)	(0.065)	(0.066)
Sigma	0.190***	0.195***	0.195***
	(0.006)	(0.007)	(0.007)

Note:

1) The dependent variable is the natural log of the number of new hires.
2) Various cases of autoregressive disturbances are applied and AR(2) is reported because more than 2 lags of the disturbances are not significant.
3) The data ranges from April 1990 to March 2012.
4) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 8: Results for Each Period by FGLS

variables	[period 1]	[period 2]	[period 3]	[period 4]	[period 5]
constant	0.983	-0.392	0.042	-1.504	-2.438
	(2.147)	(0.790)	(0.836)	(1.505)	(3.745)
ln S	-0.513	0.064	0.213**	0.048	-0.104
	(0.372)	(0.094)	(0.101)	(0.128)	(0.202)
ln V	1.293**	0.654***	0.279***	0.594***	0.933***
	(0.455)	(0.122)	(0.088)	(0.098)	(0.175)
L.ln Openness	0.169	-0.278	**-0.709****	-0.390	-0.736
	(0.456)	(0.252)	**(0.309)**	(0.352)	(0.923)
trend	0.018*	0.002*	-0.004**	0.007*	0.008
	(0.009)	(0.001)	(0.001)	(0.004)	(0.011)
Observations	19	71	59	71	38
Adjusted R^2	0.227	0.322	0.603	0.628	0.694
Rho	0.232	0.296	0.096	-0.054	-0.158
DW d-stat (original)	1.856	1.365	1.659	2.108	2.313
DW d-stat (transformed)	2.100	2.013	1.990	2.006	2.014

Note:

1) The dependent variable is the natural log of the number of new hires.
2) Period 1 is from April 1990 to December 1991, period 2 from January 1992 to December 1997, period 3 from January 1998 to December 2002, period 4 from January 2003 to December 2008, and period 5 from January 2009 to March 2012.
3) FGLS in this table uses Prais-Winsten transformation and Cochrane-Orcutt Iterative Procedure.
4) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Table 9: Results for Each Period by 2SLS

variables	[period 1]	[period 2]	[period 3]	[period 4]	[period 5]
ln Openness	-0.131	-0.437	**-1.796****	-0.493	-1.068
	(0.804)	(0.327)	**(0.789)**	(0.679)	(2.095)
ln S	-0.199	0.084	0.155	0.066	-0.112
	(0.538)	(0.071)	(0.153)	(0.145)	(0.113)
ln V	0.934	0.702***	0.257**	0.623***	0.985***
	(0.671)	(0.162)	(0.107)	(0.110)	(0.255)
trend	0.014*	0.003**	-0.002	0.007	0.009
	(0.007)	(0.001)	(0.002)	(0.006)	(0.021)
constant	-0.003	-0.968	-1.344	-1.907	-3.258
	(2.635)	(1.133)	(1.303)	(2.678)	(7.181)
Observations	19	72	60	72	39
R^2	0.3186	0.398	0.3796	0.644	0.688

Note:

1) The dependent variable is the natural log of the number of new hires.
2) Period 1 is from April 1990 to December 1991, period 2 from January 1992 to December 1997, period 3 from January 1998 to December 2002, period 4 from January 2003 to December 2008, and period 5 from January 2009 to March 2012.
3) The first and second lags of ln Openness are used for instruments.
4) *** indicates 1 percent level of significance, ** 5 percent, and * 10 percent.

Appendix

Table A1: Job-seekers, Job Vacancies, and New Hires in Employment Exchange in India (1988-2011)

year	offices	job-seekers (f)	New hires	Vacancies	Job-seekers (s)
1988	-	6062.0	327.2	543.0	30,050.0
1989	-	6574.0	290.2	600.1	32,776.0
1990	-	6237.0	261.9	493.2	34,632.0
1991	-	6237.0	253.2	458.7	36,300.0
1992	-	5301.0	238.5	419.5	36,758.0
1993	-	5934.0	231.4	384.5	36,276.0
1994	-	5929.0	204.9	396.5	36,692.0
1995	-	5558.0	214.9	385.3	36,742.0
1996	-	5872.0	233.0	424.0	37,430.0
1997	-	6324.0	274.6	412.9	39,139.9
1998	860	5852.2	233.2	358.9	40,090.0
1999	870	5967.0	221.8	327.9	40,371.0
2000	873	5064.0	168.2	283.9	41,344.0
2001	938	5554.0	185.3	312.6	41,996.0
2002	939	5064.0	147.3	220.4	41,171.0
2003	945	5462.0	154.5	255.6	41,389.0
2004	947	5375.0	139.0	275.6	40,458.0
2005	947	5436.0	175.8	349.2	39,348.0
2006	947	7287.0	180.5	358.0	41,466.0
2007	965	5413.0	263.6	525.1	39,974.0
2008	968	5315.0	304.5	570.8	39,115.0
2009	969	5692.0	261.6	419.5	38,152.0
2010	969	6187.0	326.9	707.0	38,827.0
2011	966	6206.0	469.9	819.4	40,071.0

Source: Indiastat.com (originally from DGE&T's various annual reports of "Employment Exchange Statistics").

Notes:

1) Unit for job-seekers (f), new hires, vacancies and job-seekers (s) is thousand.
2) Job-seekers (f) and job-seekers (s) denote flow value in a year and stock value at the end of each year, respectively.