Journal of Money and Economy
Vol. 13, No. 4, Fall 2018
pp. 491-499

# Job Finding and Inflow to Unemployment: The Case of Iran

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Received: 6 Feb 2019 Approved: 16 Oct 2019

To analyze the labor market through search and matching theory, we need deep parameters, namely, the rate of inflow to the unemployment pool and job-finding rate. In other words, these rates are primary parameters of matching function; hence, estimating these parameters is an essential step for the use of search and matching theory in every economy. In this paper, we estimate these rates of Iran's economy using the Simulated Method of Moments (SMM) as a baseline for future studies in this framework. We use the unemployment rate and the number of unemployed workers who were unemployed for less than one month. We find estimates of around 0.1 and 0.32 for the rate of inflow to unemployment and job-finding rate, respectively, which are lower than the amounts estimated for the United States and other developed countries. It is a sign of some labor market irregularities in Iran's economy. For example, it shows that the probability of experiencing long-term unemployment/employment by unemployed/employed ones is high because of lower job-finding and inflow to unemployment rates.

**Keywords:** Matching Theory, Labor Market, Unemployment, Unemployment Duration.
**JEL Classification:** C78, F16, J64

## 1 Introduction

Search and matching models in the labor market were introduced by Diamond (1982) and Mortensen and Pissarides (1994). This theory plays an essential role in the new unemployment theories, for it explicitly models labor market outcomes, namely unemployment, employment, job vacancies, worker flows, and transitions. Moreover, the advent of the model has encouraged the development of relevant data sets.[5] Primary inputs of these models are the rate

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[5] Further information can be found on Yashiv (2007b)

of inflow to unemployment and job-finding rate, which we provide estimates of these rates in this paper.

The variation of the unemployment rate over time can be created by the change in inflow to the unemployment rate (the rate in which workers lose their job) or/ and job-finding rate (the rate in which the unemployed find a job). The share of these rates in the variation of U.S. unemployment rate is estimated in some studies such as Elsby et al. (2009), Fujita and Ramey (2009), Hall (2005a, b), Shimer (2005, 2012), Blanchard and Diamond (1990), Davis and Holtiwanger (1990), Darby et al. (1985) and Yashiv(2007a). Some of these papers found that high rate of inflow to unemployment is the main characteristic of recessions (Blanchard and Diamond (1990), Davis and Holtiwanger (1990), Darby et al. (1985)). On the other hand, some studies such as Shimer (2005) that suggest the low job-finding rate is the reason for high unemployment. These studies highlight that the precise measurement of inflow to the unemployment rate and the job-finding rate is greatly beneficial to explain trends and fluctuations in the labor market.

Various approaches and frameworks are used to estimates parameters of a search and match model in a specific country. Hobijn and Sahin (2009) compute job-finding and separation rates for OECD countries using the GMM approach. In contrast, Elsby et al. (2013) use inflow to unemployment instead of the separation rate, and they mentioned two reasons for this difference. First, a separation typically means a quit or layoff from an employer. In the presence of job to job transitions, such termination need not lead to an unemployment spell. Second, some unemployment spells originate from non-participation rather than a separation from employment. We follow Elsby et al. (2013) in this study and estimate inflow to unemployment.

In terms of the approach, we follow Shimer (2005) that presents new measures of the parameters. He proposes two strong assumptions in his paper, which are essential in the process of his estimation; workers neither enter nor exit the labor force but transit between employment and unemployment, in any period all unemployed workers have the same job-finding probability, and all employed workers have the equal exit probability. The method of Shimer was used by some other authors afterward, such as Elsby et al. (2013). In this paper, we employ primary conditions introduced by Shimer (2005) via the SMM method to estimate inflow to the unemployment rate and job-finding rate.

There are a few studies that estimate the search and match model in Iran. For instance, Farahzadi and Rahmati (2018) estimate a structural dynamic discrete choice model of married female labor participation using microdata from Iran. They estimate the separation rates non-parametrically for various groups of their study. However, their research focuses just on a restricted sample of married females, which cannot be generalized to the whole economy. Moreover, their approach is to estimate separation rates with suffering from previously mentioned challenges. Also, Ebadi et al. (2018) expect a logical range for the job-finding and inflow to unemployment rates; besides, they highlight some probable Institutional problems in Iran's labor market. It is noteworthy that this paper uses a different method to obtain the exact value of these parameters.

Section 2 describes the model. Section 3 demonstrates how the SMM approach is employed on Iran's data. Results and discussion are presented in Section 4.

## 2 Model

Shimer (2005) introduces the following equation to discuss the dynamics of unemployment:

$$u_{t+1} = \frac{(1-e^{-f-x})x}{f+x} l_t + e^{-f-x} u_t$$

$u_{t+1}$ is unemployment in period t+1, $f$ is the job-finding rate, $x$ is the inflow to unemployment and $l_t$ is the size of the labor force, which is assumed to be constant. This theoretical equation may not hold in real data either because of heterogeneity in observations and potential mismeasurement or simplicity in the underlying assumptions. Therefore, we may add a random part ($\varepsilon_t \sim N(0,1)$) to this equation as a proxy for other factors which can affect unemployment

$$u_{t+1} = \frac{(1-e^{-f-x})x}{f+x} l_t + e^{-f-x} u_t + \varepsilon_t \quad (1)$$

Besides, we have the law of motion for unemployment as $u_{t+1} = (1-F)u_t + u_{t+1}^s$. This equation states that the number of unemployed in period t+1 is equal to the unmatched unemployed persons in period t ($(1-F)u_t$) plus the short term unemployed workers ($u_{t+1}^s$). In this Equation, $F$ is the job-finding probability and $f = -\log(1-F)$.[1] So we can assess the short-term unemployment rate from:

[1] For more information in this part refer to Shimer (2005).

$$u_{t+1}^{s} = \frac{(1-e^{-(f+x)})x}{f+x} l_t + (e^{-(f+x)} - e^{-f})u_t + \varepsilon_t \tag{2}$$

The law of motion for unemployment and Equation (2) is the necessary conditions we employ to estimate the parameters via the simulated method of moments. The next section explains the estimation strategy and data.

## 3 Estimation Strategy

We use the Simulated Method of Moments (SMM) to estimate inflow and outflow rates of unemployment. The basic idea of this model is to generate simulated series from the model and match moments of simulated series with actual moments from data. First, we should solve the model numerically as a function of unknown parameters (in our framework, the unknowns are $x$ and$f$). Therefore, the components of the estimation are:

- Actual data ($z_t$), (quarterly unemployment rate and short-term unemployment)
- Moments derived from actual data ($M_T(z)$)
- Simulate data ($y_t(b)$), (simulate unemployment rate and short-term unemployment)
- Moments derived from simulated data ($M_N(y(b))$
- Assume that $M_T(z) \xrightarrow{a.s.} \mu(z)$ when $T \to \infty$ and $M_N(y(b)) \xrightarrow{a.s.} \mu(y(b))$ when $N \to \infty$. $\mu(z)$ and $\mu(y(b))$ are population moments, $N = T \times H$ where T is the number of observed data, and H is the number of simulations.
- Through SMM, we can find true parameters among a grid of feasible values. Let $b_0$, be the vector of true parameters, then $\mu(z) = \mu(y(b_0))$, which is the link between data and theory.
- Appropriate weight as introduced by Lee and Ingram (1991) and optimization as:

$$\hat{b}_{TN} = \arg\min_{b} \left[M_T(z) - M_N(y(b))\right]' W_T [M_T(z) - M_N(y(b))]$$

In other words, a simulation estimator is an estimator that minimizes the weighted sum of squared errors of the model moments from the data moments. This estimator is a consistent and asymptotically normal estimator of $b_0$. $W_T$ is a symmetric $n \times n$ weighting matrix. We will explain this matrix below.

For estimation, we should follow these steps,

1) For any value in the feasible grid of b; $b^i$, we should simulate a series of unemployment and short-term unemployment. For making this simulation we use random draws from normal distribution as it has appeared in these series formulas and $b^i$.
2) Compute data moments and simulation moments with data and artificial series respectively and evaluate the objective function:

$$J(b^i) = \left[M_T(z) - M_N\left(y(b^i)\right)\right]' W \left[M_T(z) - M_N\left(y(b^i)\right)\right]$$

3) Choose a new value for b, for which the amount of objective function in this new value is smaller in comparison to the last value.

We should use the same random draw throughout each simulation; otherwise, we wouldn't converge to an estimate because the change in the objective function can stem from variations in draws. To derive the optimal weighting matrix (W), notice that the vector of moments is

$$m(z_t) = \begin{bmatrix} z_t \\ (z_t - \bar{z}) \\ (z_t - \bar{z})(z_{t-1} - \bar{z}) \\ (z_t - \bar{z})(z_{t-2} - \bar{z}) \end{bmatrix}$$

$M_T(z) = \frac{1}{T}\sum_{t=1}^{T} m(z_t)$ and $M_N(y(b)) = \frac{1}{H}\sum_{h=1}^{H}\frac{1}{T}\sum_{t=1}^{T} m(y_t^h(b))$ which H=20. We can estimate W in two ways:

1) Let

$$\hat{\Gamma}_{T,j} = \frac{1}{T}\sum_{t=j+1}^{T}[m(z_t) - M_T(z)][m(z_{t-j}) - M_T(z)]'$$

Denote the j-th autocovariance of m. the estimated sample variance-covariance matrix of $(m(z_t))$ is given by $\hat{S}_{z,T} = \hat{\Gamma}_{T,0} + \sum_{j=1}^{T}(1 - \frac{j}{i(T)+1})(\hat{\Gamma}_{T,j} + \hat{\Gamma}'_{T,j})$

Where $i(T)$ is the key to the Newey-West correction (is equal to 4 in this paper) and weighting matrix is $\hat{S}_{z,T}$ which we call it $W^*$. This matrix is estimated by the true data.

2) We can use simulated data for computing W. In this way, we will estimate "b", by W=I as the first step, and then with the use of this consistent "b", we can estimate the variance-covariance matrix. The weighting matrix is the inverse of the mentioned matrix.

In this paper, we use the true date for constructing the weighting matrix.

We use the unemployment rate and the number of unemployed workers who were unemployed for less than one month. The data is collected quarterly by the Statistical Center of Iran under the title of the labor force survey. We use quarterly data, and the period is from 1384-1 to 1393-1.

## 4 Results

We first draw a series of a random sample $\{\{\varepsilon_t^h\}_{t=1}^T\}_{h=1}^H$. We will use the same draw in the whole estimation process. Given the parameters' value, we can construct the desired series. Our objective is to choose $x_t$ and $f_t$ so that the weighted sum of squared residuals between the model moments and data moments is minimized (moments are described in the last part). Figure 1 plots the objective function weighted by this matrix. The values which minimize the objective function are $f = 0.32$ & $x = 0.1$, and their standard errors respectively are equal to 0.05 & 1.1.

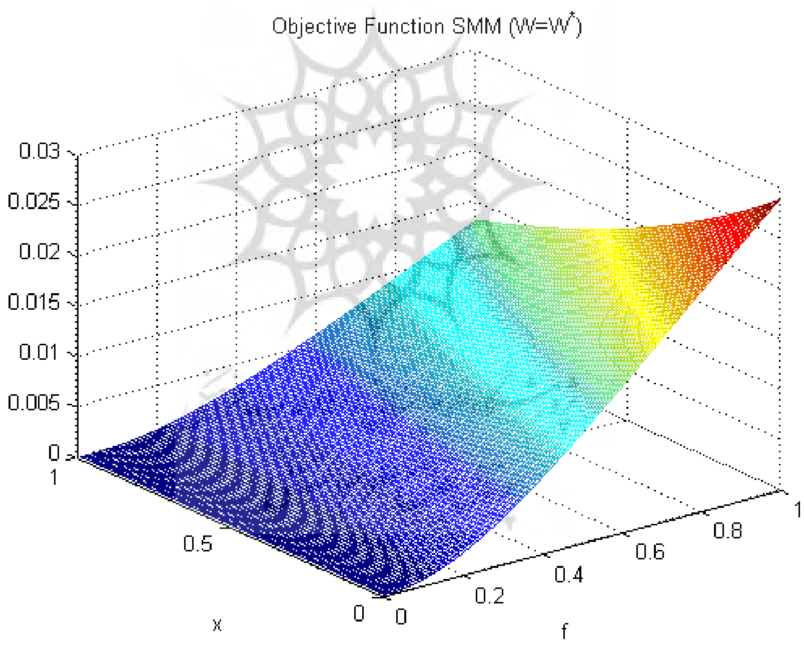


Figure 1. Objective function of the estimated method

The estimated parameters are lower than the amounts calculated for the United States, as shown in Table (1).

Table 1
*Comparing inflow to unemployment and job-finding rates for Iran and the United States*

| countries / parameters | x (inflow to unemployment) | f (job-finding rate) |
|---|---|---|
| Iran | 0.1 | 0.32 |
| United States* | 0.12 | 0.7 |

*: Blanchrd and Gali (2010)

The estimated values are different from the estimates for developed countries. It is a sign of some labor market irregularities in Iran's economy. For instance, the job-finding rate is double in the U.S. compare to Iran, which suggests high flexibility in the mature labor market. The question of what institutional framework causes this irregularity suggests a future line of research. We conjecture that the declining productivity trends in manufacturing firms (Pilevari and Rahmati 2018) and glooming prospects for future growth prevent firms from recruiting new employees.

Moreover, the government, a decade ago, was a significant player in the job market. After the new wave of privatization, stagnating firms care less about aggregate employment and prefer to stabilize their profit by economizing their laborers. Therefore, the shrinking size of the government may explain part of the decline in the job-finding rate.

## 5 Conclusion

In this paper, we provide estimates of job-finding rates and inflow to unemployment status through a simulated method of moments. We find that the forecast of job-finding rate and inflow to unemployment status are equal to 0.32 and 0.1, respectively. The former is significantly less than the corresponding estimates in developed countries. We conjecture that the low job-finding rate is because of declining productivity trends in the real economy (Pilevari and Rahmati 2018), and glooming prospects for future growth prevent firms from recruiting new employees.

Moreover, the government, a decade ago, was a significant player in the job market. After the new wave of privatization, stagnating firms care less about aggregate employment and prefer to stabilize their profit by economizing their laborers. Therefore, the shrinking size of the government may explain part of the decline in the job-finding rate. Besides, it shows that the probability of experiencing long-term unemployment/employment by unemployed/employed ones is high because of lower job-finding and inflow to unemployment rates. It should be considered that we need more studies in this field to find the underlying roots and to have precise and accurate suggestions.

These rates play a decisive role in search and matching literature; besides, they are essential features in calculating unemployment fluctuations. Hence, this paper is a fundamental one for future studies.

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