TÜRKİYE CUMHURİYET MERKEZ BANKASI

WORKING PAPER NO: 12/10

Ins and Outs of Unemployment in Turkey

March 2012

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March 2012

Abstract

This paper analyzes rates of inflow to and outflow from unemployment for Turkey since 2006. The average rate of exiting unemployment (outflow) within a month is 9.4 percent, while the average rate of transiting from employment to unemployment (inflow) is 1.3 percent. Moreover, the analysis of flow rates for different age and education groups show that these rates change significantly across groups. The paper decomposes changes in unemployment into contributions from inflow and outflow rates and finds that the volatility of inflow rates is the main driving force of the change in the unemployment rate in Turkey.

Keywords: Unemployment, Worker Flows, Job Finding Rate, Separation Rate.

JEL Code: E24, J6.

*The views expressed herein are those of the author and do not represent the official views of the Central Bank of the Republic of Turkey.

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1 Introduction

The rate of unemployment in a labor market is determined by the rate at which workers enter into unemployment (inflow), and the rate at which unemployed workers leave (outflow). These two flow rates help us understand the unemployment dynamics in that market. This paper aims to calculate the inflow and outflow rates for Turkey, analyze the unemployment experiences of different demographic groups, and the effects of these flow rates on unemployment dynamics.

There are studies that analyze unemployment dynamics of developed countries using these flow rates. For instance, Shimer (2007) finds that the most of the variation in unemployment comes from the movements in outflow rates in the U.S. from 1976 to 2007.[1] Elsby, Hobijn, and Sahin (2009) (EHS hereafter) generalize the methodology Shimer (2007) uses to evaluate flow rates for some European countries. They document that there is a natural division across countries in levels of flow rates. Anglo-Saxon and Nordic economies experience high unemployment exit rates (higher than 20 percent) while continental European countries experience much lower rates (less than 10 percent). Symmetrically, Anglo-Saxon and Nordic countries experience higher inflow rates (that exceed 1.5 percent per month) than those of continental European countries (which have inflow rates between 0.5 and 1 percent).

This paper uses monthly data from the Turkish Statistical Agency from 2005 to 2010 and extends the methodology reported in EHS to allow for changes in the labor force. The methodology makes use of time series for the labor force, the total number of unemployed, and the number of unemployed for different durations (depending on the availability of the data). Results suggest that the worker flows

[1] See also Elsby, Michaels, and Solon (2009) and Fujita and Ramey (2009).

in the Turkish labor market more closely resemble to the flows in labor markets of Continental European countries, rather than those of Anglo-Saxon and Nordic countries. The average monthly unemployment exit rate is 9.4 percent while the entry rate is 1.3 percent. I also analyze the flow rates for different education and age groups. Workers with a higher level of education have lower entry rates to unemployment, while workers with the lowest level of education have, on average, the highest exit rates. Younger workers have higher unemployment and inflow rates, while their job finding opportunities are similar to those of an older ages.

The paper also decomposes the variation in unemployment rate into variation in inflow and outflow rates, following the methodology used in EHS. Since 2006, the unemployment fluctuations in Turkey result mainly from the changes in the rate at which employees separate from their jobs to unemployment. Contributions of inflow and outflow rates are around 80:10, while these contributions are around 55:45 for many of the continental European and Nordic countries, and 15:85 for the U.S.(see EHS). However, since the data for Turkey covers a relatively short period of time, the strong effect of separations on unemployment dynamics should be interpreted cautiously.

The rest of the paper is organized as follows: The next section describes the data and the methodology used to compute the inflow and outflow rates. It is followed by a section that describes the results. Section 4 is about the variance decomposition of the unemployment rate. The final section concludes.

2 Inflow and Outflow Rates

The paper uses the number of labor force and the number of unemployed persons for less than d months, where $d \in \{1, 3, 6, 9, 12\}$, which are from the Household

Labor Force Survey of the Turkish Statistical Agency.[2] The data is for different education groups, age groups, and urban vs. rural residence. There is also data for males for the last two groups. The female unemployment by duration data is not well captured by the Household Labor Survey. Hence survey results for females are not used in this study. Throughout the paper, the unemployed fraction of the labor force that has an unemployment duration less than d months in month t is denoted by $u_t^{<d}$.[3]

2.1 Methodology

I use the method proposed by Shimer (2007) and by EHS to find the monthly flow rates. Let time be continuous, and let the data be available at discrete dates t. Hence, "period t" refers to the interval $[t, t+1)$. Moreover, let f_t and s_t be the job arrival and job destruction rates during period t. Also let $L_{t+\tau}$, $U_{t+\tau}$, and $U_t^{<1}(\tau)$ be the number of labor force, the number of unemployed, and the number of unemployed for less than 5 weeks at time $t+\tau$, respectively.

Both Shimer (2007) and EHS assume a constant labor force in their analysis. While this may be a reasonable assumption for developed countries, flows in and out of labor force may matter in developing countries like Turkey. However, the data does not allow for modeling the flows between labor force and inactivity

[2]For more information, go to www.turkstat.gov.tr. $d = 1$ corresponds to the number of workers unemployed for less than 5 weeks and this data is distributed by the TurkStat upon request.

[3]The series are seasonally adjusted with Tramo/Seats method. As such, the number of employed workers is computed as the difference between the labor force and the total number of unemployed, then the number of employed and unemployed are seasonally adjusted, and aggregated to get the seasonally adjusted labor force. As the number of employed and unemployed have different seasonal dynamics in Turkey, aggregating seasonally adjusted employment and unemployment series is preferable to seasonally adjusting the labor force series itself. The series are also seasonally adjusted using X12 method developed by Census Bureau. Quantitative results change only slightly, while their qualitative nature doesn't change.

explicitly. To get around data limitations and still investigate the possible effects of changes in the labor force, I assume that the labor force grows at a rate g_t and some a fraction of the change in the labor force joins to the unemployed (hence, the remaining directly becomes employed). Since the data on a is not available, a is assumed to be constant. Flow rates are calculated for different values of a and the implications are discussed in the later sections.

We can write the system of differential equations as:

$$\begin{aligned}
\dot{L}_{t+\tau} &= g_t L_{t+\tau}, && (1)\\
\dot{U}_{t+\tau} &= (L_{t+\tau} - U_{t+\tau})s_t - U_{t+\tau} f_t + a\dot{L}_{t+\tau}, && (2)\\
\dot{U}_t^{<1}(\tau) &= (l_{t+\tau} - U_{t+\tau})s_t - U_t^{<1}(\tau) f_t + a\dot{L}_{t+\tau}. && (3)
\end{aligned}$$

The first equation formalizes the change in the labor force, while the second equation displays the law of motion for the unemployment rate. At any time, unemployment changes because some s_t fraction of employees become unemployed (the first term on the right hand side of the second equation), some f_t fraction of unemployed leaves the pool (the second term), and a fraction of the change in the labor force is absorbed by the unemployment state (the last term). The third equation shows the change in the number of unemployed for less than one month, which consists of workers separating from their jobs, workers who became unemployed after the last time data was available and did not leave unemployment, and workers who join the labor force, respectively. Observe that g_t, f_t, and s_t are assumed to be constant between t and $t + \tau$.

Observe that adding equations (2) and (3) results in:

$$\dot{U}_{t+\tau} = \dot{U}_t^{<1}(\tau) - (U_{t+\tau} - U_t^{<1}(\tau))f_t. \tag{4}$$

Solving the differential equation (and rewriting the equation in terms of rates) yields:

$$u_t = e^{-f_t - g_t} u_{t-1} + u_t^{<1}, \tag{5}$$

where u_t denotes the unemployment *rate* in period t.

If a job arrives with a Poisson process with parameter f_t, then the probability of finding a job within a month is $F_t = 1 - e^{-f_t}$. Therefore, equation (5) can be rewritten as

$$F_t = 1 - \frac{u_t - u_t^{<1}}{e^{-g_t} u_{t-1}}. \tag{6}$$

The change in the labor force affects the outflow rate, while the fraction of change in the labor force that is due to entry and exit through unemployment (a) doesn't appear in the outflow equation. This is not because this fraction does not affect the flow per se, but it is because the number of short term unemployed in the subsequent period already contains entrants to the labor market through unemployment. Hence, F_t captures the flows out of unemployment, regardless of their destination. Since some of the outflow may be due to the inactivity, the job finding probability will somehow be smaller than the outflow probability.

The monthly outflow probability relates to associated monthly outflow hazard rate, $f_t^{<1}$, through the following equation:

$$f_t^{<1} = -ln(1 - F_t). \tag{7}$$

2.1.1 Estimating Flow Hazard Rates

Equation (6) works well to estimate the outflow probability in labor markets for which the flow rate out of unemployment is high (duration of unemploy is low). For countries with longer duration, there are relatively few people in $u_t^{<1}$ at any time since exit rates are low.[4] Hence the variance of the estimate will be higher (F will be noisy). EHS use additional duration data to increase the precision of the estimate of F_t. Based on the unemployment data by duration, we can calculate the probability that an unemployed worker exits unemployment within d months as

$$F_t^d = 1 - \frac{u_t - u_t^{<d}}{e^{-\sum_{j=0}^{d-1} g_{t-j}} u_{t-d}} \tag{8}$$

As before, we can calculate the outflow rates as

$$f_t^{<d} = -ln(1 - F_t^d)/d, \tag{9}$$

for $d = 1, 3, 6, 9, 12$.

If the exit rate from unemployment is independent of the duration of unemployment, then $f_t^{<d}$ for different values of d would not be much different from each other, and we have the monthly outflow hazard rate as $f_t^{<1}$. However, if the exit rate from unemployment depends on the duration of unemployment, then the $f_t^{<1}$ rate would not be a consistent estimate of the average outflow rate. I formally test the duration dependence by testing the hypothesis that $f_t^{<1} = f_t^{<3} = f_t^{<6} = f_t^{<9} = f_t^{<12}$. Formal details of the test are discussed in the appendix. The approach in general is to derive the asymptotical distribution of unemployment rates and unemployment rates for different durations, and then to apply the Delta method to compute the joint asymptotic distribution of the outflow rate estimates. For Turkey, the hypothesis that there is no duration dependence can rejected at 95% confidence level. Then, I use the asymptotic

[4]For the U.S., on average, around 43 percent of all unemployed are unemployed for less than 5 weeks for the period 1976 to 2008. The short term fraction of unemployed in Turkey averages to 17 percent from 2006 to 2010.

distribution to compute an optimally weighted estimate of outflow rate that minimizes the mean squared error of the estimate.

After computing the value of f_t, equation (2) is solved to get an equation for the job separation rate as

$$u_t = e^{-f_t-s_t-g_t}u_{t-1} + \frac{(1-e^{-f_t-s_t-g_t})(ag_t+s_t)}{f_t+s_t+g_t}. \tag{10}$$

Note that if $g_t = 0$, i.e., if we assume that the labor force is constant, we get the original equations of EHS. Also note that a affects the rate of flows from employment into unemployment. If a is small (large), then the most of the changes in the labor force will be absorbed by the (un)employment. In this case, the separation will have higher (lower) levels, as we need more (do not need as many) flows from employment to unemployment in order to account for the change in unemployment.

3 Results

I compute the monthly flow rates as described in the previous section. I calculate flow rates under two different assumptions about a. First, I assume that $a = 0$, i.e., all changes in the labor force is absorbed by employment. I also calculate flow rates, assuming that $a = 1$, i.e., all changes in the labor force is absorbed by unemployment.[5]

The average unemployment rate in Turkey is 11.5 percent over the 2006-2010 period. Among all unemployed, the fraction that is unemployed for less than 5

[5]For some months, the difference between change in unemployment and change in the labor force are such that unemployment cannot absorb all of the change. Since setting $a = 1$ implies a negative inflow rate in these cases, I set a to its maximum value that will imply a nonnegative inflow rate.

weeks is 17 percent, on average. 28 percent of all unemployed have a duration of 3 months or less. People who are unemployed for longer than 3 months, but shorter than 6 are 26 percent of the unemployed. 12 and 4 percent of the unemployed experience unemployment for 7 to 8 months and 9 to 11 months, respectively. Almost 30 percent of the unemployed workers suffer from unemployment for a year or longer. Although there is significant change in labor force annually, the monthly changes in labor force in Turkey is small. Since the data is in monthly frequency, the effect of change in labor force on quantitative results is also small.

Table 1: Results: Overall Economy

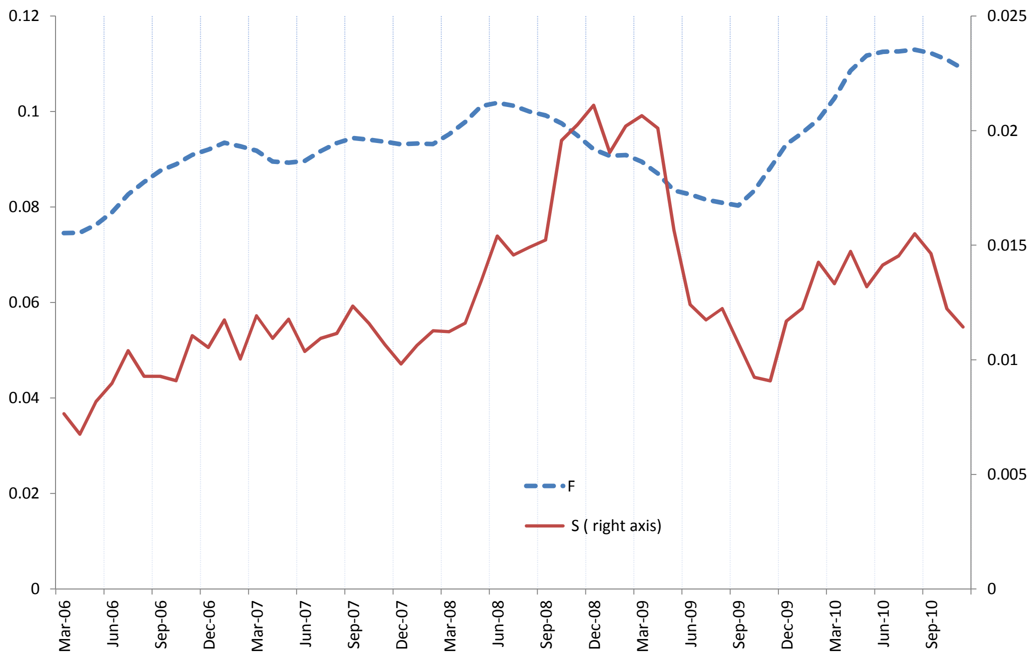
u	F	$S(a = 0)$	$S(a = 1^*)$
0.115	0.091	0.013	0.010
(0.016)	(0.01)	(0.003)	(0.004)

*: For some months, the difference between change in unemployment and change in labor force are such that unemployment cannot absorb all of the change in labor force. Since setting $a = 1$ implies a negative inflow rate in these cases, I set a to its maximum value that will imply a nonnegative inflow rate.

I report the estimates of inflow and outflow rates as three-month moving averages of the monthly unemployment rate and the flow rates in Table 1. The average probability that an unemployed worker finds a job within the next month is 9 percent. The average probability that an employed worker separates from her job to unemployment is 1.3 percent, if we assume $a = 0$. These inflow and outflow rates are close to the rates for France, Germany, Spain and Portugal (EHS). Hence, in terms of flows in and out of unemployment, the Turkish labor market is closer to the labor markets in continental Europe than those in Anglo-Saxon countries (EHS).

Figure 1 shows the job finding and separation probabilities ($a = 0$) over the sample period. We observe that both the job finding and separation probabilities were increasing before the crisis. Effects of these increases were almost canceling

Figure 1: Flow Rates



3-month moving averages of monthly inflow (S) and outflow (F) probabilities, where $a = 0$.

each other out as the unemployment rate was not changing much during this period (Figure 2).

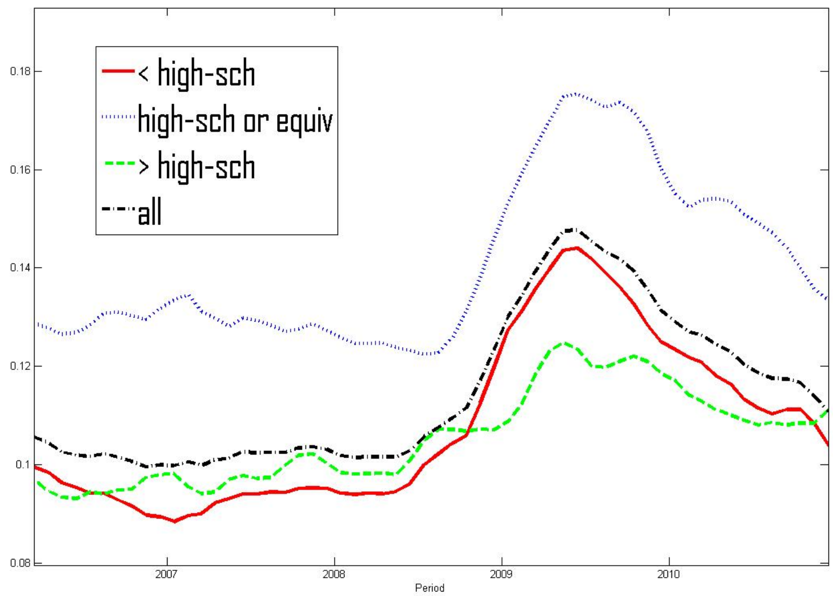
If we assume $a = 1$, then the average inflow probability drops to 1 percent. As discussed earlier, the value of a does not affect the estimates of f_t, while it affects both the level and the volatility of the inflow rate.[6] The results for the cases $a = 0$ and $a = 1$ imply that the level is affected more. For the rest of the paper results for $a = 0$ are discussed, unless stated otherwise, as $a = 1$ does not affect the quantitative nature of the results much.

[6]Comparison of different outflow series for different values of a show that inflow rate is higher for lower values of a for the majority of the data and sometimes it is slightly lower.

3.1 Unemployment dynamics by education

This subsection analyzes the unemployment and flow rates in and out of unemployment for three different education groups. These groups are: workers without a high school or equivalent diploma, workers with a high school or equivalent occupational school degree, and workers with degrees in higher education. On average, 64 percent of the labor force in Turkey does not have a high school degree and workers with higher education form 15 percent of the labor force.[7]

Figure 2: Unemployment rate by education groups



Educational attainment is an important factor affecting workers' labor market outcomes. The theory suggests that workers with higher educational attainment, who are assumed to have higher skills, should have an advantageous position in the form of wages and unemployment rates, compared to their counterparts with lower educational attainment. When we look at the the unemployment rates by

[7]The share of workers without higher education degrees is declining over time.

education groups in Turkey (Figure 2), we see that workers with a high school or equivalent occupational school diploma experience the highest unemployment rate, while workers without a high school degree have almost the same unemployment rate as workers with higher degrees.

Table 2 shows inflow and outflow rates of these education groups as well as their unemployment rates (graphs of the flow rates by education are displayed in the appendix). The first observation is that workers with higher education have lower job separation probabilities compared to other groups. However, these workers experience almost the same, if not lower, unemployment exit probabilities as the other education groups. We also see that workers without a high school diploma have, on average, better chances of leaving unemployment, while workers with a high-school or equivalent diploma are the ones most likely to separate from their jobs.

Table 2: Results by Education

	$<$ **high sch.**	$\equiv$ **high sch.**	$>$ **high sch.**	**All**
shares	0.60	0.27	0.13	
	(0.01)	(0.02)	(0.01)	
u	0.11	0.14	0.11	0.12
	(0.02)	(0.02)	(0.01)	(0.02)
F	0.10	0.08	0.07	0.09
	(0.01)	(0.01)	(0.01)	(0.01)
$S(a=0)$	0.013	0.014	0.010	0.013
	(0.003)	(0.004)	(0.003)	(0.003)
$S(a=1)$	0.011	0.013	0.006	0.010
	(0.005)	(0.006)	(0.004)	(0.004)

Numbers in parentheses are the standard errors.

The salient feature of these results is the lack of a monotone relationship between the unemployment rate and education in Turkey. However, this analysis is silent about the source of non-monotonicity. The reason behind the non-monotonicity could be due to relatively low unemployment of low education groups and/or relatively high unemployment rate of other groups. One plausible explanation, that needs further investigation, is that the education system cannot deliver the skills that are compatible with the needs of the labor market, whereas the lower educated group can gain such skills through apprenticeship. Tansel (2004) looks at data from 1988 to 2002 and finds that the unemployment rate for high school graduates is the highest, while the unemployment rate for the low education group is the lowest in Turkey for that period. However, she documents the unemployment rate of college graduates to be the lowest in urban areas. Given that Turkey has been going under economic and educational transformation since 1980s, the effect of education on unemployment in Turkey, as well as its effect on other labor market outcomes, needs more investigation.

3.2 Unemployment dynamics by age

This study also analyzes the unemployment dynamics of different age groups in the labor market. Young workers (workers between the ages of 15 and 25 in this analysis) are expected to have a higher unemployment rate, as they are expected to change jobs (and/or careers), while workers at the prime age (between 25 and 54) are expected to have lower unemployment rates.[8] I also look at data for male labor force participants, especially those at the prime age (ages between 25 and 54). Since female labor force has issues of its own (such as non-persistent change in participation rates, possible tenure breaks due to maternity), looking at data for only male workers provides a robustness check on the findings of the paper.[9]

[8]Due to sampling issues in LFS, values for older workers are not computed.

[9]For details about the labor market experiences of females in Turkey see, for instance, Baskaya and Sengul (2012).

Table 3 displays the results for all the labor force and also for males only. First note that, since females are a small fraction of the labor force, results for both genders and results for males are similar. Hence, I discuss only the results for male labor force participants. First of all, we see that young workers are almost two times more likely to be unemployed than the older workers. Notice that young workers have similar outflow rates while they are almost three times more likely to loose their jobs. High separation rates is the main reason of the relatively high unemployment rate that young workers experience, compared to adults.[10]

Table 3: Results by age

	All			**Males**		
	15-24	**25-54**	**all**	**15-24**	**25-54**	**all**
shares	0.30	0.56		0.31	0.65	
	(0.02)	(0.02)		(0.02)	(0.01)	
u	0.19	0.09	0.12	0.21	0.10	0.11
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
F	0.08	0.07	0.09	0.11	0.10	0.10
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$S(a=0)$	0.02	0.007	0.013	0.032	0.011	0.014
	(0.006)	(0.002)	(0.006)	(0.008)	(0.003)	(0.004)
$S(a=1)$	0.02	0.004	0.01	0.032	0.010	0.012
	(0.008)	(0.003)	(0.004)	(0.01)	(0.003)	(0.004)

3.3 Unemployment dynamics in Rural and Urban Areas

The share of the agricultural sector in employment is still large in Turkey.[11] Thus, there is a possibility that dynamics of labor markets may be clouded by the movements in the agricultural sector, which has its own dynamics. Hence, it is informative to look at labor market conditions for non-agricultural workers.

[10]Young workers may have more adverse experiences in finding jobs, nonetheless, unemployment exit rate is not the main reason for their relatively high unemployment rate.

[11]It is around 25 percent, which is the highest in OECD.

Unfortunately, the data in Turkey does not allow for such direct analysis. Instead, I rely on the data TurkStat provides for urban and rural areas. On average, 80 percent of the labor force resides in urban areas in Turkey. Most of the agriculture is done in rural areas and the share of agriculture in total employment is around 25 percent. Although noisy, data for urban areas is a good proxy for non-agricultural labor markets.

Table 4: Results by Area of Residence

	All	**Urban**	**Rural**
shares		0.79	0.21
		(0.008)	(0.008)
u	0.12	0.14	0.07
	(0.02)	(0.02)	(0.01)
F	0.09	0.09	0.10
	(0.01)	(0.01)	(0.02)
$S(a=0)$	0.013	0.015	0.008
	(0.003)	(0.004)	(0.002)
$S(a=1)$	0.010	0.013	0.007
	(0.004)	(0.004)	(0.004)

As Table 4 displays, unemployment in urban areas is higher than the overall average unemployment rate. This is expected, as the unemployment in agriculture is low in Turkey. The average job finding probability in urban areas is very close to the national average, while job separation is above the average. Nonetheless, these results, coupled with the flow rates for prime age males, suggest that the Turkish labor market has low flow rates across employment states.

4 Contributions of Ins and Outs to Unemployment Volatility

In this section, I analyze how the variations in the unemployment rate are affected by the flow rates. To compute the contributions of flow rates to the volatility of unemployment, one needs to apply a formal decomposition of changes in unemployment into parts due to changes in inflow and outflow rates. Such decomposition is straightforward if we use the steady state unemployment rate instead of the actual rate. This can be done for countries like the U.S., where flows are large, and hence steady state unemployment rate is a very good approximation for the actual unemployment rate. Thus, variance decomposition of steady state unemployment rate, which is simple, suffices for countries with high worker flows (see EHS for more details). However, for countries with low flow rates the unemployment dynamics would be slow, making steady state unemployment rate a poor approximation for the actual unemployment rate. As EHS shows, using decomposition for the steady state unemployment rate in these cases may give misleading results as it ignores the changes in unemployment that results from dynamics associated with the unemployment rate moving towards its steady state level. EHS use a decomposition that takes into account the changes due to the deviation of the unemployment rate from its steady state level. I use the monthly flow rates computed in the previous section and the decomposition suggested by EHS, as flow rates for Turkey are also low, to analyze the contributions of and outs to the unemployment volatility.

4.1 Variance Decomposition

To find the contributions of changes in flow rates to the change in unemployment rate, I log-linearize the equation 10. The result of this linearization is:

$$\Delta ln(u_t) = \left(1 - e^{-\theta_{t-1}}\right)\left[\Delta ln(u_t^*) + \frac{-e^{-\theta_{t-2}}}{\left(1 - e^{-\theta_{t-2}}\right)}\Delta ln(u_{t-1})\right], \tag{11}$$

where $\Delta ln(u_t^*)$ is defined in equation (A.17) and $\theta_t = f_t + s_t + g_t$, for notational convenience. This equation is a version of the decomposition used by EHS that is modified to accommodate the effect of changes in labor force. Details of the calculation are given in the appendix.

We can find the decomposition of unemployment changes using equation 11 and the methodology of EHS to get

$$\begin{aligned} \beta_f &= \frac{cov(\Delta lnu_t, \quad C_{f,t})}{var(\Delta lnu_t)}, \quad \beta_s = \frac{cov(\Delta lnu_t, \ C_{s,t})}{var(\Delta lnu_t)}, \\ \beta_g &= \frac{cov(\Delta lnu_t, \ C_{g,t})}{var(\Delta lnu_t)}, \quad \beta_o = \frac{cov(\Delta lnu_t, \ C_{o,t})}{var(\Delta lnu_t)}, \end{aligned} \tag{12}$$

where β_f, β_s, β_g, and β_o are the fractions of volatility in unemployment that are due to contributions from outflows, inflows, the labor force growth, and steady state adjustment respectfully. $C_{f,t}$, $C_{s,t}$, $C_{g,t}$, and $C_{o,t}$ denote the respective cumulative contributions of contemporaneous and past variations in the inflow rate, the outflow rate, and the labor force growth rate, as well as the deviation from steady state at $t = 0$. They are defined recursively as follows:

$$C_{f,t} = \Big(1 - e^{-\theta_{t-1}}\Big)\Big[- \frac{f_{t-1} u^*_{t-1}}{f_{t-1} + s_{t-1} + g_{t-1}} \Delta ln(f_t) + \frac{e^{-\theta_{t-2}}}{1 - e^{-\theta_{t-2}}} C_{f,t-1}]\Big], \quad C_{f,0} = 0 \tag{13}$$

$$C_{s,t} = \Big(1 - e^{-\theta_{t-1}}\Big)\Big[\frac{s_{t-1}(1 - u^*_{t-1})}{f_{t-1} + s_{t-1} + g_{t-1}} \Delta ln(s_t) + \frac{e^{-\theta_{t-2}}}{1 - e^{-\theta_{t-2}}} C_{s,t-1}]\Big], \quad C_{s,0} = 0 \tag{14}$$

$$C_{g,t} = \Big(1 - e^{-\theta_{t-1}}\Big)\Big[\frac{g_{t-1}(a - u^*_{t-1})}{f_{t-1} + s_{t-1} + g_{t-1}} \Delta ln(g_t) + \frac{e^{-\theta_{t-2}}}{1 - e^{-\theta_{t-2}}} C_{g,t-1}]\Big], \quad C_{g,0} = 0 \tag{15}$$

$$C_{o,t} = \Big(1 - e^{-\theta_t} \frac{e^{-\theta_{t-1}}}{1 - e^{-\theta_{t-1}}} C_{o,t-1}]\Big], \quad C_{o,0} = \Delta ln(u_0). \tag{16}$$

If the decomposition fully captures the fluctuations in unemployment rate then $\beta_f + \beta_s + \beta_g + \beta_o = 1$. The analysis shows that when all the change in labor force is absorbed by unemployment, the variance decomposition above is not a good approximation as $\beta_f + \beta_s + \beta_g + \beta_o$ is away from 1.[12] Hence, I report values only for $a = 0$ below.

4.2 Results

Table 5 shows variance decomposition results for different age groups, Table 6 displays the result for different education groups, while Table 7 analyzes the population residing in different areas. Since results of the decomposition is qualitatively the same across all groups, I evaluate them together. The first three columns in all three tables are for the whole sample period, which is from 2006 to 2010. First, observe that the sum of the coefficients is close to 1, thus we can conclude that the approach described above is a good approximation of the variance decomposition.

The first row of the results show that the change in labor force doesn't contribute to the variation in unemployment. This result is not surprising as monthly

[12]It is a good approximation for some of the subgroups analyzed. Since the results doesn't change qualitatively for these groups, compared to the case where $a = 0$, I omit reporting these groups as well.

Table 5: Variance Decomposition Results by Age

	2006-2010			2006-2007			2008-2010		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
β_g	0	0	0	0	0	0	0	0	0
β_f	0.10	0	0.16	0.12	-0.04	0.19	0.12	-0.04	0.18
β_s	0.84	1.05	0.78	0.86	1.23	0.65	0.82	0.96	0.75
β_o	0	0	-0.06	0	-0.01	0.03	0	0.01	-0.01
$\sum$	0.93	1.06	0.87	0.98	1.19	0.87	0.94	0.92	0.92

(1): Ages 15 to 24. (2): Ages 25 to 54. (3): All age groups

change in labor force is quite small. The table clearly shows that the main contributor to the volatility of unemployment rate is the volatility due to separation rate. Moreover, the contribution of separations is stronger in Turkey compared to those we observe in Continental European countries (EHS). Consequently, the contribution of outflow rates to variability of unemployment is relatively low in Turkey.

Table 6: Variance Decomposition Results by Education

	2006-2010			2006-2007			2008-2010		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
β_g	0	0		0	0	0	0	0	0
β_f	0.12	0	0.17	0.12	-0.02	0.21	-0.04	-0.05	-0.02
β_s	0.79	0.93	0.70	1.03	1.42	0.81	1.10	1.15	1.08
β_o	0	0.01	0.01	0	-0.01	-0.03	0.01	0	-0.03
$\sum$	0.91	0.94	0.88	1.15	1.4	0.99	1.07	1.1	1.03

(1): Less than high school degree. (2): High school or equivalent degree. (3): More than high school degree

As one may wonder whether the results of the variance decomposition is dominated by the movements during the crisis, I also do the variance decomposition for the pre- and post-crisis era. Columns from 5 to 7 show the decomposition for the pre-crisis period (years 2006 and 2007), while the last three columns show the results for the post-crisis sample. The results show that for all sub-samples,

Table 7: Variance Decomposition Results by Urban

	2006-2010			2006-2007			2008-2010		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
β_g	0	0	0	0	0	0	0	0	0
β_f	0.12	-0.04	0.18	0.11	-0.10	0.19	0.05	0.01	0.11
β_s	0.82	0.96	0.76	0.91	1.30	0.77	0.86	0.77	0.80
β_o	0	0.02	-0.01	-0.01	-0.02	0	-0.01	0.02	-0.02
$\sum$	0.94	0.93	0.92	1.02	1.19	0.96	0.90	0.79	0.89

(1): All. (2): Urban areas. (3): Rural areas.

the main reason behind the volatility of unemployment is the variation in inflow rates. During the crisis this effect gets stronger for the overall sample, highly and low educated, and for urban residents.

5 Conclusion

This paper analyzes inflow and outflow rates of unemployment for Turkey using the monthly data from the Turkish Labor Force Survey for the period from 2005 to 2010. Using employment data and unemployment data by duration of unemployment, I compute the time series of the probability that an unemployed worker leaves unemployment within the next month, and the probability that an employed worker becomes unemployed within the subsequent month.

The paper also analyzes the flow rates for different demographic groups. As expected, the young workers have a higher unemployment rate than their older counterparts. The reason for this is not that they leave unemployment slowly (their probability of exiting unemployment is similar to those of older workers), but because they have higher probabilities of separating from their jobs. Although workers with higher education have slightly lower unemployment rates, they are not as advantageous in the market as their counterparts in other countries.[13]

In addition to flow rates, the paper analyzes the contributions of inflow and outflow rates of unemployment to its volatility. Results suggest that, for variations in the unemployment rate in Turkey, the inflow rate into unemployment is the dominant factor. This fact holds true both for the pre- and the post-crisis era, as well as for all demographic groups.

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[13]For instance, Layard, Nickell, and Jackman (1991, p. 44) show that in the U.S. and in the U.K., unemployment among blue collar workers is twice as high as it is among white collar workers.

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A Appendix

A.1 Details of Estimating Flow Hazard Rates

Asymptotical Distribution of Outflow Hazard Rates: We can rewrite estimates of hazard rates as:

$$
\begin{aligned}
f_t^{<1} &= -[ln(u_t - u_t^{<1}) - ln(u_{t-1}e^{-g_{t-1}})], \\
f_t^{<3} &= -[ln(u_t - u_t^{<3}) - ln(u_{t-3}e^{-\sum_{j=0}^{2} g_{t-j}})]/3, \\
f_t^{<6} &= -[ln(u_t - u_t^{<6}) - ln(u_{t-6}e^{-\sum_{j=0}^{5} g_{t-j}})]/6, \\
f_t^{<9} &= -[ln(u_t - u_t^{<9}) - ln(u_{t-9}e^{-\sum_{j=0}^{8} g_{t-j}})]/9, \\
f_t^{<12} &= -[ln(u_t - u_t^{<12}) - ln(u_{t-12}e^{-\sum_{j=0}^{11} g_{t-j}})]/12.
\end{aligned}
$$

Let us define, u_{dt} such that, $u_{1t} = u_t^{<1}$, $u_{3t} = u_t^{<3} - u_{1t}$, etc. We can rewrite the equations above in terms of u_{dt}:

$$
\begin{aligned}
f_t^{<1} &= -[ln(u_{3t} + u_{6t} + u_{9t} + u_{12t} + u_{\infty t}) - ln(u_{t-1}e^{-g_{t-1}})], \\
f_t^{<3} &= -[ln(u_{6t} + u_{9t} + u_{12t} + u_{\infty t}) - ln(u_{t-3}e^{-\sum_{j=0}^{2} g_{t-j}})]/3, \\
f_t^{<6} &= -[ln(u_{9t} + u_{12t} + u_{\infty t}) - ln(u_{t-6}e^{-\sum_{j=0}^{5} g_{t-j}})]/6, \\
f_t^{<9} &= -[ln(u_{12t} + u_{\infty t}) - ln(u_{t-9}e^{-\sum_{j=0}^{8} g_{t-j}})]/9, \\
f_t^{<12} &= -[ln(u_{\infty t}) - ln(u_{t-12}e^{-\sum_{j=0}^{11} g_{t-j}})]/12.
\end{aligned}
$$

Moreover, let u_{dt} be the population value. These numbers are approximated by estimates $\hat{u}_{dt}$ using the survey sample with size n_t. Let us assume that the sample size is constant, and let us denote the duration with d and lags with s. These sample approximations have a joint multinominal distribution, such that

$$E(\hat{u}_{dt}) = u_{dt}, \qquad E(\hat{u}_{t-s}) = \frac{u_{t-s}}{e^{\sum_{j=1}^{s} g_{t-j}}},$$

$$var(\hat{u}_{dt}) = \frac{1}{n} u_{dt}(1 - u_{dt}), \qquad cov(\hat{u}_{dt}, \hat{u}_{d't}) = \frac{-1}{n} \hat{u}_{dt} \hat{u}_{d't},$$

$$var(\hat{u}_{t-s}) = \frac{1}{n} \frac{u_{t-s}}{e^{\sum_{j=1}^{s} g_{t-j}}} \frac{(1 - u_{t-s})}{e^{\sum_{j=1}^{s} g_{t-j}}}, \qquad cov(\hat{u}_{dt}, \hat{u}_{t-s}) = 0, \qquad cov(\hat{u}_t, \hat{u}_{t-s}) = 0.$$

Define the vector

$$\bar{u}_t = [u_{1t}, u_{3t}, u_{6t}, u_{9t}, u_{12t}, u_{\infty t}, u_{t-3} e^{-\sum_{j=0}^{2} g_{t-j}}, u_{t-6} e^{\sum_{j=0}^{5} g_{t-j}}, u_{t-9} e^{-\sum_{j=0}^{8} g_{t-j}}, u_{t-12} e^{-\sum_{j=0}^{11} g_{t-j}}]',$$

and the covariance vector

$$\bar{V}_t = \begin{bmatrix} \bar{V}_t^d & \bar{0}_{6x4} \\ \bar{0}_{4x6} & \bar{V}_t^u, \end{bmatrix}$$

where

$$\bar{V}_t^d = \begin{bmatrix} u_{1t}(1-u_{1t}) & -\hat{u}_{1t}\hat{u}_{3t} & -\hat{u}_{1t}\hat{u}_{6t} & -\hat{u}_{1t}\hat{u}_{9t} & -\hat{u}_{1t}\hat{u}_{12t} & -\hat{u}_{1t}\hat{u}_{\infty t} \\ -\hat{u}_{1t}\hat{u}_{3t} & u_{3t}(1-u_{3t}) & -\hat{u}_{3t}\hat{u}_{6t} & -\hat{u}_{3t}\hat{u}_{9t} & -\hat{u}_{3t}\hat{u}_{12t} & -\hat{u}_{3t}\hat{u}_{\infty t} \\ -\hat{u}_{1t}\hat{u}_{6t} & -\hat{u}_{3t}\hat{u}_{6t} & u_{6t}(1-u_{6t}) & -\hat{u}_{6t}\hat{u}_{9t} & -\hat{u}_{6t}\hat{u}_{12t} & -\hat{u}_{6t}\hat{u}_{\infty t} \\ -\hat{u}_{1t}\hat{u}_{9t} & -\hat{u}_{3t}\hat{u}_{9t} & -\hat{u}_{6t}\hat{u}_{9t} & u_{9t}(1-u_{9t}) & -\hat{u}_{9t}\hat{u}_{12t} & -\hat{u}_{9t}\hat{u}_{\infty t} \\ -\hat{u}_{1t}\hat{u}_{12t} & -\hat{u}_{3t}\hat{u}_{12t} & -\hat{u}_{6t}\hat{u}_{12t} & -\hat{u}_{9t}\hat{u}_{12t} & u_{12t}(1-u_{12t}) & -\hat{u}_{12t}\hat{u}_{\infty t} \\ -\hat{u}_{1t}\hat{u}_{\infty t} & -\hat{u}_{3t}\hat{u}_{\infty t} & -\hat{u}_{6t}\hat{u}_{\infty t} & -\hat{u}_{9t}\hat{u}_{\infty t} & -\hat{u}_{12t}\hat{u}_{\infty t} & u_{\infty t}(1-u_{\infty t}) \end{bmatrix},$$

and

$$\bar{V_t^u} = \begin{bmatrix} \frac{u_{t-3}(1-u_{t-3})}{e^{2\sum_{j=1}^{3} g_{t-j}}} & 0 & 0 & 0 \\ 0 & \frac{u_{t-6}(1-u_{t-6})}{e^{2\sum_{j=1}^{6} g_{t-j}}} & 0 & 0 \\ 0 & 0 & \frac{u_{t-9}(1-u_{t-9})}{e^{2\sum_{j=1}^{9} g_{t-j}}} & 0 \\ 0 & 0 & 0 & \frac{u_{t-12}(1-u_{t-12})}{e^{\sum_{j=1}^{12} g_{t-j}}} \end{bmatrix}.$$

Assuming that n is large, we can approximate

$$\sqrt{n}(\hat{\bar{u}}_t - \bar{u}_t) \to N(0, \bar{V}_t),$$

such that

$$\hat{\bar{u}}_t \sim N\Big(\bar{u}_t, \frac{1}{n}\bar{V}_t\Big).$$

Now, define a vector

$$\bar{f}_t = [f_t^{<1}, f_t^{<3}, f_t^{<6}, f_t^{<9}, f_t^{<12}]'.$$

We will use Delta method to drive the asymptotical distribution of $\bar{f}_t$. Consider the following gradient:

$$\bar{D}_{ft} = \frac{\partial \bar{f}_t}{\partial \bar{u}_t{}'} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ \frac{-1}{\hat{u}_t - \hat{u}_t^{<1}} & 0 & 0 & 0 & 0 \\ \frac{-1}{\hat{u}_t - \hat{u}_t^{<1}} & \frac{-1}{3(\hat{u}_t - \hat{u}_t^{<3})} & 0 & 0 & 0 \\ \frac{-1}{\hat{u}_t - \hat{u}_t^{<1}} & \frac{-1}{3(\hat{u}_t - \hat{u}_t^{<3})} & \frac{-1}{6(\hat{u}_t - \hat{u}_t^{<6})} & 0 & 0 \\ \frac{-1}{\hat{u}_t - \hat{u}_t^{<1}} & \frac{-1}{3(\hat{u}_t - \hat{u}_t^{<3})} & \frac{-1}{6(\hat{u}_t - \hat{u}_t^{<6})} & \frac{-1}{9(\hat{u}_t - \hat{u}_t^{<9})} & 0 \\ \frac{-1}{\hat{u}_t - \hat{u}_t^{<1}} & \frac{-1}{3(\hat{u}_t - \hat{u}_t^{<3})} & \frac{-1}{6(\hat{u}_t - \hat{u}_t^{<6})} & \frac{-1}{9(\hat{u}_t - \hat{u}_t^{<9})} & \frac{-1}{12(\hat{u}_t - \hat{u}_t^{<12})} \\ 0 & \frac{1}{3\hat{u}_{t-3}} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{6\hat{u}_{t-6}} & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{9\hat{u}_{t-9}} & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{12\hat{u}_{t-12}} \end{bmatrix}'.$$

This allows us to write the approximate distribution

$$\hat{\bar{f}}_t \sim N\Big(\bar{f}_t, \frac{1}{n}\bar{D}_{ft}\bar{V}_t\bar{D}'_{ft}\Big).$$

Hypothesis Testing for No Duration Dependence: If there is no duration dependence , then

$$H_0 : \quad \bar{f}\iota = f\iota, \ \text{ where } f \text{ is a scalar and the } \iota \text{ is a vector with ones,}$$

which is the null hypothesis. Define the following matrix:

$$\bar{M}_f = \begin{bmatrix} 1 & 0 & 0 & 0 & -1 \\ 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 & -1 \\ 0 & 0 & 0 & 1 & -1 \end{bmatrix}.$$

Then, under the null,

$$\bar{M}_f \hat{\bar{f}}_t \sim N\Big(0, \frac{1}{n} \bar{M}_f \bar{D}_{ft} \bar{V}_t \bar{D}'_{ft} \bar{M}'_f\Big).$$

The Wald statistic becomes:

$$g_t = n \hat{\bar{f}}'_t \bar{M}'_f \Big(\bar{M}_f \bar{D}_{ft} \bar{V}_t \bar{D}'_{ft} \bar{M}'_f\Big)^{-1} \bar{M}_f \hat{\bar{f}}_t.$$

Under the null, $g_t \sim \chi^2(4)$.

Optimal weights: If we reject the null that there is no duration dependence, we need to estimate the optimal weights to get the job finding probability. We want to find $\bar{\omega}$ and estimate

$$f_t = \bar{\omega}'_t \bar{f}_t,$$

such that $\bar{\omega}'_t \iota = 1$, and given this, $\bar{\omega}$ minimizes

$$V_f = \bar{\omega}_t \bar{D}_{ft} \bar{V}_t \bar{D}'_{ft} \bar{\omega}'_t.$$

To take care of the first restriction, define

$$\tilde{\bar{\omega}}_t = [\omega_t^{<1}, \omega_t^{<3}, \omega_t^{<6}, \omega_t^{<9}]',$$

such that

$$\bar{\omega}_t = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -1 & -1 & -1 & -1 \end{bmatrix} \tilde{\bar{\omega}}_t,$$

$$\bar{\omega}_t = \bar{e}_1 + \bar{M}_w \tilde{\bar{\omega}}_t.$$

Then the objective can be written as

$$V_f = \bar{e}_1' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{e}_1 + 2\bar{e}_1' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w \tilde{\bar{\omega}}_t + \tilde{\bar{\omega}}_t' \bar{M}_w' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w \tilde{\bar{\omega}}_t,$$

which yields optimal weighting matrix of

$$\tilde{\bar{\omega}}_t = -(\bar{M}_w' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w)^{-1} \bar{M}_w' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w \bar{e}_1,$$

and thus

$$\bar{\omega}_t = \bar{e}_1 - \bar{M}_w (\bar{M}_w' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w)^{-1} \bar{M}_w' \bar{D}_{ft} \bar{V}_t \bar{D}_{ft}' \bar{M}_w \bar{e}_1.$$

A.2 Dynamic Decomposition of Changes in Unemployment

We log-linearize the equation below around $t-1$, where $s_t = s_{t-1}$, $f_t = f_{t-1}$, $g_t = g_{t-1}$, and $u_{t-1} = u_{t-1}^*$.

$$u_t = e^{-f_t - s_t - g_t} u_{t-1} + \frac{(1 - e^{-f_t - s_t - g_t})(a g_t + s_t)}{f_t + s_t + g_t}.$$

The steady state unemployment rate is $u_t^* = \frac{ag_t + s_t}{s_t + f_t + g_t}$. For notational convenience, let us define $\theta_t = f_t + s_t + g_t$. We can rewrite the equation above as

$$u_t = e^{-\theta_t} u_{t-1} + (1 - e^{-\theta_t}) u_t^*,$$

and $u_t^* = \frac{a_t g_t + s_t}{\theta_t}$. Log-linearize the equation for u_t around $t-1$:

$$\begin{aligned} ln(u_t) = ln(u_{t-1}^*) + \frac{1}{u_{t-1}^*}\Big[& u_{t-1}^*\big(ln(u_{t-1}) - ln(u_{t-1}^*)\big)e^{-\theta_{t-1}} \\ & + f_{t-1}\Delta ln(f_t)(1 - e^{-\theta_{t-1}})\frac{-ag_{t-1} - s_{t-1}}{\theta_{t-1}^2} \\ & + s_{t-1}\Delta ln(s_t)(1 - e^{-\theta_{t-1}})\frac{f_{t-1} + g_{t-1} - ag_{t-1}}{\theta_{t-1}^2} \\ & + g_{t-1}\Delta ln(g_t)(1 - e^{-\theta_{t-1}})\frac{af_{t-1} + as_{t-1} - s_{t-1}}{\theta_{t-1}^2}\Big] + \epsilon_t, \end{aligned}$$

where $\Delta ln(x_t) = ln(x_t) - ln(x_{t-1})$. Rearrange these terms to get:

$$\begin{aligned} ln(u_t) = {} & ln(u_{t-1}^*) + \big(ln(u_{t-1}) - ln(u_{t-1}^*)\big)e^{-\theta_{t-1}} \\ & + \frac{1 - e^{-\theta_{t-1}}}{u_{t-1}^*}\Big[f_{t-1}\Delta ln(f_t)\frac{-a_{t-1}g_{t-1} - s_{t-1}}{\theta_{t-1}^2} \\ & + s_{t-1}\Delta ln(s_t)\frac{f_{t-1} + g_{t-1} - a_{t-1}g_{t-1}}{\theta_{t-1}^2} + g_{t-1}\Delta ln(g_t)\frac{a_{t-1}f_{t-1} + a_{t-1}s_{t-1} - s_{t-1}}{\theta_{t-1}^2}\Big] + \epsilon_t. \end{aligned}$$

Notice that log linearizing steady state unemployment rate yields:

$$\begin{aligned} ln(u_t^*) = {} & ln(\frac{ag_{t-1} + s_{t-1}}{\theta_{t-1}}) + \frac{1}{\frac{ag_{t-1} + s_{t-1}}{\theta_{t-1}}}\Big[f_{t-1}\Delta ln(f_t)\frac{-ag_{t-1} - s_{t-1}}{\theta_{t-1}^2} \\ & + s_{t-1}\Delta ln(s_t)\frac{f_{t-1} + g_{t-1} - ag_{t-1}}{\theta_{t-1}^2} + g_{t-1}\Delta ln(g_t)\frac{af_{t-1} + as_{t-1} - s_{t-1}}{\theta_{t-1}^2}\Big] + \eta_t, \end{aligned}$$

where $\frac{ag_{t-1}+s_{t-1}}{\theta_{t-1}} = u^*_{t-1}$.

$$\begin{aligned} ln(u^*_t) - ln(u^*_{t-1}) = \frac{1}{u^*_{t-1}} \Big[& f_{t-1}\Delta ln(f_t)\frac{-ag_{t-1}-s_{t-1}}{\theta^2_{t-1}} \\ & + s_{t-1}\Delta ln(s_t)\frac{f_{t-1}+g_{t-1}-ag_{t-1}}{\theta^2_{t-1}} \\ & + g_{t-1}\Delta ln(g_t)\frac{af_{t-1}+as_{t-1}-s_{t-1}}{\theta^2_{t-1}}\Big] + \eta_t. \end{aligned} \tag{A.17}$$

Hence, we can rewrite the equation for $ln(u_t)$ as follows:

$$ln(u_t) = ln(u^*_{t-1}) + \big(ln(u_{t-1}) - ln(u^*_{t-1})\big)e^{-\theta_{t-1}} + \big(1-e^{-\theta_{t-1}}\big)\big(ln(u^*_t) - ln(u^*_{t-1})\big) + \epsilon^{'}_t,$$

$$ln(u_t) - ln(u_{t-1}) = -\big(1-e^{-\theta_{t-1}}\big)\big(ln(u_{t-1}) - ln(u^*_{t-1})\big) + \big(1-e^{-\theta_{t-1}}\big)\big(ln(u^*_t) - ln(u^*_{t-1})\big) + \epsilon^{'}_t.$$

We can further manipulate this equation to get an expression for a change in unemployment rate away from steady state:

$$\begin{aligned} ln(u_t) - ln(u_{t-1}) = & \quad \big(1-e^{-\theta_{t-1}}\big)\big(ln(u^*_t) - ln(u^*_{t-1})\big) - (1-e^{-\theta_{t-1}})\big(ln(u_t) - ln(u^*_{t-1})\big) \\ & + (1-e^{-\theta_{t-1}})\big(ln(u_t) - ln(u_{t-1})\big) + \epsilon^{'}_t, \\ ln(u_t) - ln(u_{t-1}) = & \ -\big(1-e^{-\theta_{t-1}}\big)\big(ln(u_t) - ln(u^*_t)\big) + (1-e^{-\theta_{t-1}})\big(ln(u_t) - ln(u_{t-1})\big) + \epsilon^{'}_t. \end{aligned}$$

Hence,

$$ln(u_t) - ln(u^*_t) = \frac{-e^{-\theta_{t-1}}}{\big(1-e^{-\theta_{t-1}}\big)}\big(ln(u_t) - ln(u_{t-1})\big).$$

Thus, we can rewrite the linearized equation for unemployment rate as

$$\Delta ln(u_t) = \big(1-e^{-\theta_{t-1}}\big)\Big[\Delta ln(u^*_t) + \frac{-e^{-\theta_{t-2}}}{\big(1-e^{-\theta_{t-2}}\big)}\Delta ln(u_{t-1})\Big], \tag{A.18}$$

where $\Delta ln(u^*_t)$ is defined in equation (A.17).

Figure A.3: Inflow Rates by Education

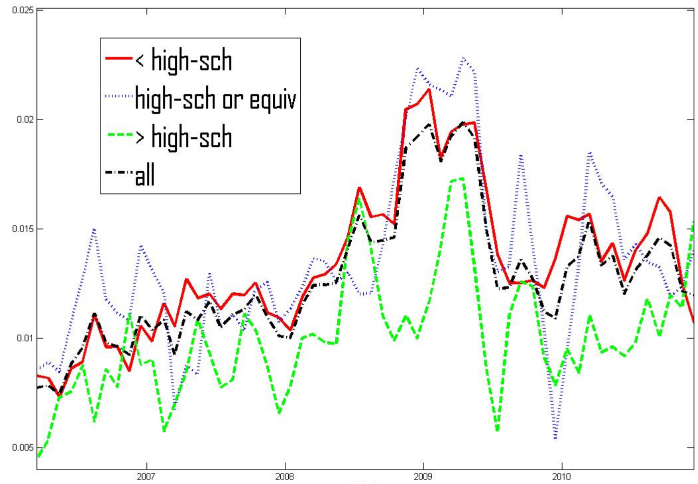


Figure A.4: Outflow Rates by Education

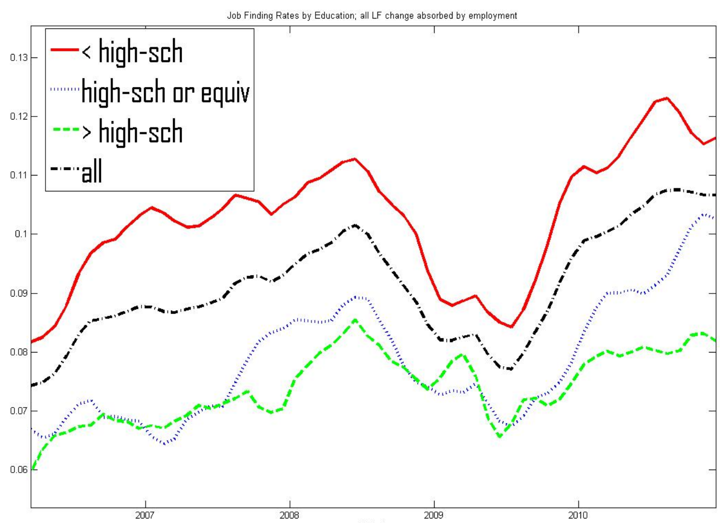


Figure A.5: Inflow (left) and Outflow (right) Rates by Age

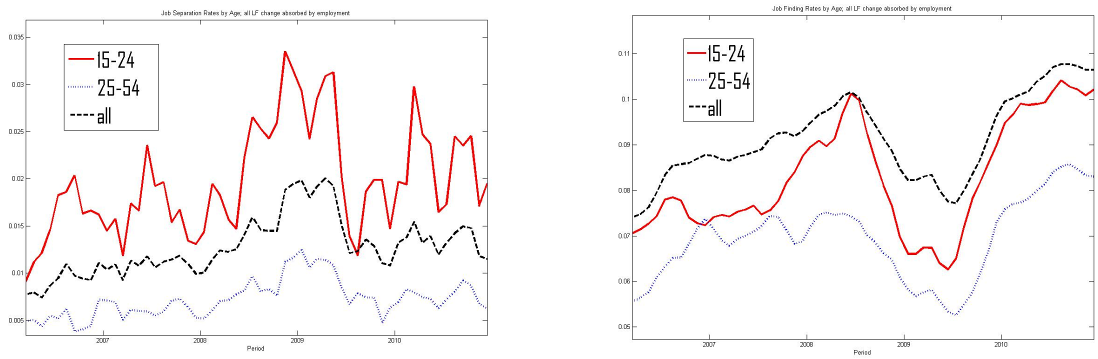


Figure A.6: Male Inflow (left) and Outflow (right) Rates by Age

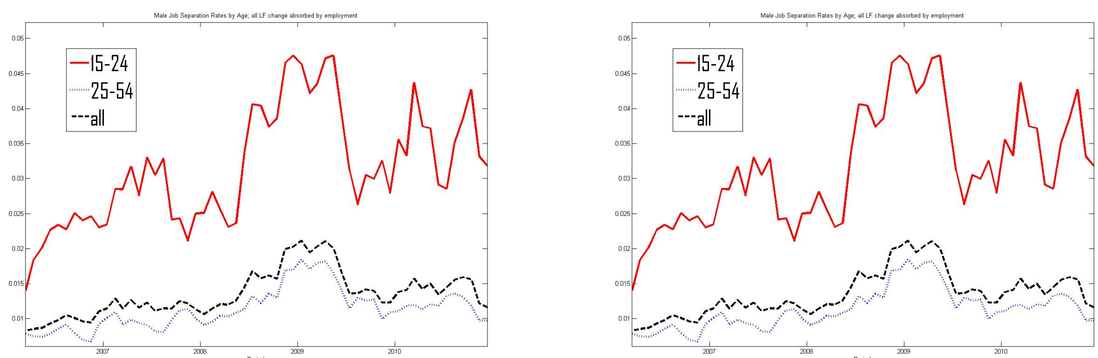


Figure A.7: Inflow (left) and Outflow (right) Rates by Residence

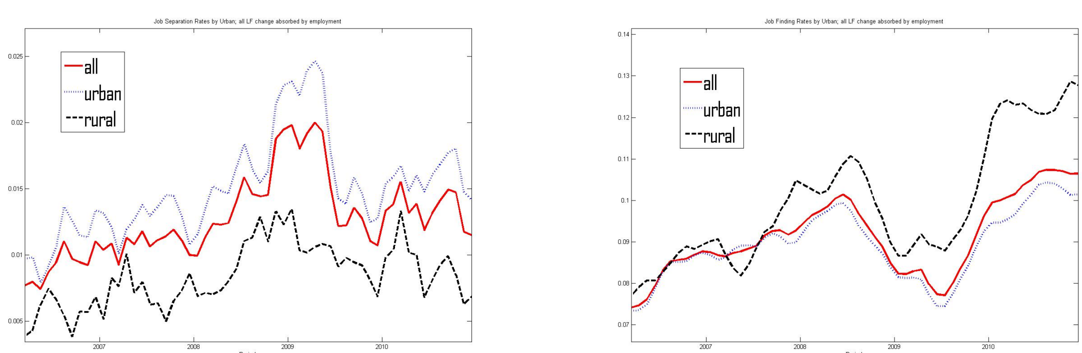


Figure A.8: Unemployment Rates by Age

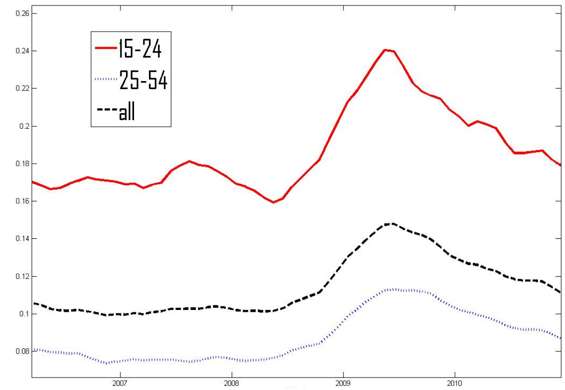


Figure A.9: Unemployment Rates by Age; Males

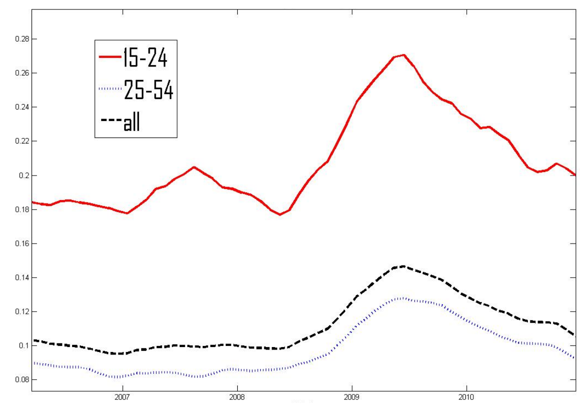
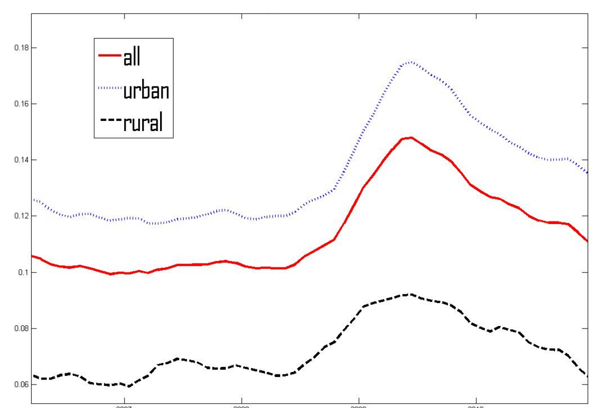


Figure A.10: Unemployment Rates by Residence



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