Reforming Employment Protection in Egypt: An Evaluation Based on Transition Models with Measurement Errors *

François Langot[†]   Shaimaa Yassin[‡]

April 2016

Abstract

Do reforms introducing more flexibility into the labor markets of developing countries reduce unemployment? This paper proposes to evaluate the new Egyptian labor market law which was introduced in 2003, aiming to enhance the flexibility of the hiring and firing processes. The Egypt labor market panel surveys (ELMPS 2006 and ELMPS 2012) are used to measure the impact of this reform on the dynamics of separation and job finding rates, and to quantify their contributions to overall unemployment variability. Using longitudinal retrospective panel datasets created from the the 2006 and 2012 cross-sections and by overlapping the two surveys, we estimate annual and semi-annual transition probabilities of workers among employment, unemployment and inactivity labor market states. A unique novel model is built to correct for the recall and design bias observed in the retrospective data, using a Simulated Method of Moments (SMM). Using the "corrected" data , we show that the reform increases significantly the separation rates in Egypt but leads to non-significant effects on the job finding rates. The combined net effect is therefore an increase in the levels of the Egyptian unemployment rate: separations increase whereas hirings remain unchanged. This partial failure of the liberalization of the Egyptian labor market is then explained by an increase in the set-up costs, interpreted as a capture by the corrupt agent of the new surplus.

JEL Classification: J6, E24.

Keywords: unemployment, separation, job finding, Egypt new labor law, measurement error, corruption.

*This work has benefited from a financial grant from the Economic Research Forum. The contents and recommendations do not necessarily reflect the views of the Economic Research Forum. We thank R. Assaad, D. Margolis, F. Postel-Vinay, F. Fontaine and J. Wahba for helpful comments as well as seminar participants at University of Paris 1 Pantheon-Sorbonne (CES), Paris School of Economics and University of Maine (GAINS-TEPP). Participants at the Economic Research Forum workshop «Impact of Labor Market Regulations and Institutions on Labor Market Performance and Outcomes» and World Bank conference on «Markets, Labor and Regulations» also provided valuable remarks and suggestions.

†University of Maine (GAINS-TEPP & IRA), Paris School of Economics, Banque de France and IZA. Email: flangot@univ-lemans.fr.

‡University of Paris 1 Pantheon-Sorbonne (CES), University of Maine (GAINS-TEPP) and Paris School of Economics. Currently at University of Neuchâtel. Email: cyassine.eco@gmail.com.

1 Introduction

The history of institutions in most developing countries led their labor markets to be very rigid, where private sector contractual opportunities approached the rules of public sector appointments. Major international organizations have therefore encouraged reforms, to introduce more flexibility in these labor markets. The importance of ensuring a healthy dynamic labor market lies in creating more productive jobs and destroying less productive ones (see Veganzones-Varoudakis and Pissarides (2007)). Increased dynamics also scales down the difference between formal employment and informal work, which is very flexible by definition. By attracting more workers to formal jobs, the shift of employment into the formal sector allows an increase in the fiscal revenues of governments and hence reduces their budgetary deficits.

The importance of a more flexible labor market was recognized by the Egyptian Government in 2003, as they introduced a new labor law (No.12). The new Egypt labor law came to action in 2004 aiming at increasing the flexibility of the hiring and firing processes in Egypt. The law provides comprehensive guidelines for recruitment, hiring, compensation and termination of employees. It directly addresses the right of the employer to terminate an employee's contract and the conditions in which it performs under.

Although flexible employment protection strategies have been recommended, economic theory predicts ambiguous effects of increased flexibility on the performance of labor markets. Indeed, when the policy change is perfectly anticipated, the conventional model of Mortensen and Pissarides (1994) shows that facilitating the termination of employees leads to increased job finding rates, but also has a direct positive effect on transitions from employment to unemployment. Since the employment rate is an increasing function of job finding rates but a decreasing function of separations, evaluating a policy that increases labor market flexibility necessitates the analysis of the different elasticities of these two rates of transitions to the reform in question. **Even if the policy change is unexpected, given that the hirings and separations are jump variables, the same reasoning applies.** Even if the effects on unemployment are ambiguous, the liberalization of the labor market promotes new job and hence high productivity.

It hence becomes crucial to assess the adjustment of the Egyptian overall separation and job finding rates (the two main components of Egypt's unemployment rate) to such a more flexible employment protection strategy, introduced by the new 2003 labor law. Very few earlier studies, for example Wahba (2009) and Wahba and Assaad (2015), investigated the short term impact of the law and only on the formalization process in Egypt. The direct impact of the law on the flexibility of the hiring and firing processes in the Egyptian labor market (which was the main objective of the law) was however never addressed. Our paper is able to reply to the following research questions:

1. Investigate the evolution of worker flows trend over the period 1998-2012, and link changes in the job finding and separation rates to the New Egyptian Labor Law implemented in 2004.

2. Build up a model in a way that enables us to simulate labor market policies and examine their implications on dynamics of the Egyptian labor market.[1]

From a methodological point of view, the construction of the observed labor market transitions from microeconomic data, as developed by Shimer (2005, 2012), seems to be a perfect fit to assess this type of labor market reforms. It's a methodology that allows to exploit rich labor market surveys, to disentangle the changes in all transitions and to deduce using a simple balance of flows, the impact on aggregates, such as the rate of unemployment. In this paper, we try to use this construction methodology, to create aggregate flows from microeconomic surveys in the spirit of the work of Shimer. From an econometric point of view, the reform will be analyzed as a break in the series of job finding and separation rates. The aggregated effect on unemployment will be deduced from the composition of the differentiated effects of transition rates.

The originality of our work lies in the construction of the flow dynamics time series of the Egyptian labor market. As in most countries in the project development process, micro surveys which trace the history of each individual every month are unavailable. Only a labor market panel survey where individuals report their retrospective and current accounts of their labor market states is repeated almost every 6 years. Even with high quality collection methods and accurate cross-validated questions, such surveys and retrospective information are subject to a memory bias (recall error).[2] De Nicola and Giné (2014) have shown that the magnitude of the recall error increases over time, in part because respondents resort to inference rather than memory. Their findings are based on a comparison between administrative records and retrospective survey data from a developing country, more precisely a sample of self-employed households engaged in fishing in costal India. Using data of a developed country (USA), Poterba and Summers (1986) find through audits of employment surveys that correcting employment self-reports can change the estimated duration of unemployment by a factor of two. Thus, the methodological contribution of our paper is to propose an original method correcting this recall error, using the markovian structure of the labor market transitions. We structurally estimate using Simulated Method of Moments (SMM) a function representing the "forgetting rate" conditional on the individual's state in the labor market. Our model is close to the one developed by Magnac and Visser (1999). Given the importance of taking into consideration the entry and exit of the labor force, in an attempt to portray the Egyptian labor market as fully as possible, and to test the robustness of our method, we extend our analysis to a three-state model of the labor market (employment, unemployment and inactivity) and check if the results on unemployment rates, reconstructed from a series of corrected labor market flows, are consistent. We show that estimates of corrections then yield similar results, suggesting that our statistical correction method produces robust series. Consequently, we can conclude that our method can

[1] This can be made without any problem concerning the Lucas (1976) criticism because separation and job finding rates are jump variables, and given that the policy change is unexpected.

[2] Given the long time interval between the waves of the survey, we can not use simple methods of memory bias correction used in annual surveys to reconstruct monthly data from retrospective calendars. See e.g. Hairault, Le Barbanchon, and Sopraseuth (2013) for such methods applied on French data.

be applied to multiple surveys only available between two relatively spaced dates (points in time), which is often the case in developing countries.

The paper uses the Egypt labor market panel surveys (ELMPS 2006 and ELMPS 2012) to extract annual and semi-annual synthetic retrospective panel data sets over the period 1999-2012. As mentioned above, given the nature of our data (with a wave repeated almost every 6 years), we were concerned with recall error. We were also concerned by a potential design bias in our data due to the very rich information obtained about the most recent employment/non-employment vector versus relatively limited information about past trajectories. We hence develop our novel methodology to correct for the "recall and design" error in the labor market transitions time series.

In his 2012 article, Shimer shows that reconstructing workers flows from microeconomic surveys gives the advantage to job finding rates in explaining fluctuations of the US unemployment. His results therefore contrast with those obtained by Blanchard and Diamond (1990) and Davis and Haltiwanger (1990, 1992): these authors showed that, based on statistics of job creations and destructions (job flows), the majority of fluctuations in the US unemployment rate arise from the job destruction rate. In our article, despite the use of a methodology similar to that proposed by Shimer (2012), we show that the new 2003 labor law had significant positive effects on the separation rates, but barely any on the job finding rates. The increase in separation rates therefore outweighs the no significant change in job finding rates leading to an increase in the unemployment rates after the reform. These results are valid whether we include or exclude the inactivity state from our analysis. By performing counterfactuals analysis, we show evidence of the increasing dominant role of the separation rates in accounting for Egyptian unemployment fluctuations. It's important to note however that the separation and job finding rates remain at extremely low levels reflecting a very rigid nature of the Egyptian labor market.

These empirical results can be viewed as inconsistent with the usual Mortensen and Pissarides (1994) model, where an increase in the labor market flexibility (modeled as a downward shift of the firing costs) would definitely increase the separation and the finding rates. Indeed, such a policy which reduces tax distortions should lead as well to increasing the match surplus (even if the job duration will be reduced), and consequently the job finding rate. At this point, it becomes therefore difficult to explain the no change in job finding rates even though there has been a decrease in the firing costs using the conventional Mortensen and Pissarides (1994) model. It's true one can explain this by the time lag between the employers reaction to the reform between separating more workers directly after the implementation of the policy and hiring more workers only when they feel confident enough about the market. However, among the possible explanations behind such an observed unusual phenomenon could be the fact that Egypt is a developing country where corruption is one of the main barriers to business encountered by the entrepreneurs. We show theoretically how the Mortensen and Pissarides (1994) can account for this phenomenon and hence to match our data.[3]

The rest of the paper is divided as follows. The second section surveys the literature and exposes the value added by our paper. Section 3 briefly presents the data used in our analysis, the creation of the synthetic retrospective panel data sets and the potential error treatments. Section 4 discusses the presence of recall and design bias in our transition matrices and hence a model is built and estimated to correct for the bias. Section 5 explores the econometric methodology adopted. Section 6 presents our estimation methodology and results. Section 7 provides counterfactual experiments and policy implications. Section 8 surveys the (Mortensen and Pissarides, 1994) theoretical model and shows how it fails to explain our empirical results, except if we introduce corruption. We then finally conclude.

2 Value Added and Literature Survey

Egypt has long been ranked as a country with very rigid labor laws (see WorldBank (2014)). This has stemmed from the time when virtually all industrial employment was public sector and heavily unionized. In 1990, the private sector accounted at most for 23 percent of Egypt's manufacturing sector output, and 25 percent of its employees. Very bureaucratic rules were established. Fear of social costs of privatization may have kept these rules rigid, especially the costs of paying off fired workers.[4] Different labor regulations indices have unsurprisingly shown that Egypt, was ranked one of the most rigid among the MENA region countries, which are themselves the most restrictive developing countries, after the Latin American region (see (Veganzones-Varoudakis and Pissarides, 2007) and (Campos and Nugent, 2012))[5]. This index decreases substantially to reach a level lower than 1.5 during the period 2000-2004 after a long period of stagnation around a level of 1.8 for about three decades since 1970. Indeed, the Law 12 of the New 2003 Labor Code seems to have relatively reduced the state's role, giving greater leeway to employers to hire and fire.[6] With such a reform, should an employer need to go out of business, he gets the right to lay off all workers. In case of economic necessity, an employer has the right to lay off workers or modify contracts given

[3]Another way to explain this puzzle is to extend the Mortensen and Pissarides (1994) to account for the informal and public sectors, which represent big shares of employment. Even though the policy is directed to the formal private sector, it surely affects the interaction and the flow of workers between the different employment sectors. The conventional aggregate Mortensen and Pissarides (1994) model fails to explain the inside story of these inter-sectoral transitions. Langot and Yassin (2015) attempt to extend the Mortensen and Pissarides (1994) to model the different transitions between the formal, informal and public sectors and hence try to explain the possible reasons behind only separations increasing in response to a more flexible labor market.

[4]The crisis of the beginning of the 90's, compelled the government to look to the International Monetary Fund (IMF), World Bank and the Paris Club for support, where Egypt was required to undergo a structural adjustment package as a counterpart to receiving a stand-by credit. The result was an increase in economic activity, and strong growth in private-sector manufacturing. By 2003, the share of the Egyptian total industrial value added reached 70 percent and employment increased substantially to 60 percent.

[5]Veganzones-Varoudakis and Pissarides (2007) underline the ranking of the different developing country regions from the least to the most rigid as follows: South Asia (1.25), Sub-Saharan Africa (1.45), East Asia (1.6), MENA (1.65), Latin America (2.05), with the index of labor market regulation between parenthesis.

[6]The new 2003 law also gives greater leeway to employers to set wages and benefits.

that he provides a notice period of 2 months for an employee of less than 10 years seniority, and 3 months if seniority is over 10 years. Severance payments of an amount of 1 month per year for workers with less than 5 years experience and of an amount of 1.5 months per year after that are implemented (see WorldBank (2014) for more details).

Unfortunately , the impact of the new 2003 labor market reform has been rarely assessed. It's extremely important to measure whether the policy has achieved its direct objective on the labor market's flexibility in general, the separation and finding rates in particular, as well as it's consequent effect on the national unemployment. Policy evaluation techniques necessitate the availability of time series labor market flows to detect structural changes in a given labor market. In a country like Egypt where available data and analyses are hinged on static, cross-sectional and aggregate approaches, our mission becomes difficult. The limitations and potential errors synthetic panel data, constructed from retrospective accounts, are subject to, prevents research from confirming trends and results obtained by simple descriptive statistics[7]. Previous research as a result hardly satisfied the urge to explore the true story of the dynamics of the Egyptian Labor market and the effect of reforms on the labor market outcomes. This paper therefore aims at enriching the existing literature and exploring the effect of the new labor law implemented in 2004 on separation and job finding rates, about which we know very little from the official aggregate data and statistics (Yassin (2014) and Assaad, Krafft, and Yassin (2015)).

The paper also overcomes the budget constraints limiting annual data collection to follow workers through their careers by benefiting from the existing two waves of the Egypt Labor Market Panel Survey (2006 and 2012) as well as by the improved techniques we adopt to construct trajectory panels for individuals within these surveys from the retrospective accounts to provide us with annual panel data sets. Our techniques don't limit to only capturing these trajectories and labor market dynamics but also to correcting the recall and design[8] bias from which our retrospective data tend to suffer.[9] Like previous research, as for example De Nicola and Giné (2014), we were concerned by the recall bias observed in our retrospective calendars. Uncorrected preliminary descriptives might give false impressions about the dynamics of worker flows and unemployment in Egypt. In the literature on measurement error in transition models, two approaches are used. The first approach,

[7]See Assaad, Krafft, and Yassin (2015) for detailed evidence on how different labor market statuses, especially unemployment, are prone to misreporting over time, comparing retrospective and contemporaneous data for the same individuals over time using the Egypt Labor Market Panel Surveys 1998, 2006 and 2012.

[8]Recall bias is defined as respondents mis-reporting their retrospective trajectory because they tend to forget some events or spells, especially the short ones. The design bias arises from the fact that different types of questions are being asked for current versus recall/retrospective statuses. There is therefore a question of salience/cognitive recognition by the respondents where by asking the questions differently, respondents, or even sometimes the enumerators themselves, can interpret them differently. Yassin (2014) and Assaad, Krafft, and Yassin (2015) show for instance that due to the questionnaire design of the ELMPS, statuses in the retrospective sections are being interpreted more of job statuses rather than labor market states.

[9]In an investigation of the effect of measurement error on poverty transitions in the German Socio-Economic Panel (GSOEP), Rendtel, Langeheine, and Berntsen (1998) conclude that approximately half of the observed transitions are due to measurement error. Lollivier and Daniel (2002) corroborate this result for the European Community Household Panel (ECHP).

in the tradition of the seminal papers of Poterba and Summers (1986, 1995), uses either validation or reinterview data (assuming that these data is error free) to estimate the measurement error. While Poterba and Summers (1986) use the reinterview data from the Current Population Survey to study the impact of measurement error on the estimated number of labor market transitions, Magnac and Visser (1999) use prospective and retrospective data for the same time period to study labor mobility of French workers with the Labor Force Survey, where the prospective data was being treated as error-free. The second approach, used for example by Rendtel, Langeheine, and Berntsen (1998), is applied when no auxiliary (error-free) information is available. Based on the assumption of the Independent Classification Errors[10], these methods use latent Markov model with measurement error. In Magnac and Visser (1999) and Bassi, Hagenaars, Croon, and Vermunt (2000), this method is extended to the case where correlation between errors are possible, also by using retrospective data.

Nevertheless, these methods are designed for short term analysis of the labor market (the impact of the business cycle on labor market transitions). They use surveys where annual waves are available, and which include intra-annual information. In this perspective, the measurement error can be approximated as a small noise, with an update each year at the time of the interview. In our case, the delay between the two interviews is much longer, requiring a new method to correct for long-term memory recall bias. In addition to the recall bias, we also suspect a potential design bias in our constructed synthetic panel data sets, due to differences in the nature of questions asked about the current or most recent labor market status and those asked about the individuals' histories. We therefore add to the existing literature by applying a new theoretical model to correct for the bias observed in our data, for both a two-state and a multiple state labor market. Empirically, the technique we use to extract a retrospective panel and correct for "recall and design" bias using the Egyptian Labor market data sets would definitely allow researchers and policy-makers (who use the same or similar data sets) to use these data sets for further research and needed investigations about labor market dynamics. We also use the cross-sectional information obtained from a third wave of the Egypt Labor Market Panel Survey in 1998, to verify the results we obtain using our corrected transition rates time series. We explain in the data section the limitations of this data set and why we choose not to use it in our econometric estimations.

3 Data and Sample Selection

Our paper relies on the Egypt Labor Market Panel Surveys 1998, 2006 and 2012, the first, second and third rounds of a periodic longitudinal survey that tracks the labor market and demographic characteristics of households and individuals interviewed in 1998. The households selected in the longitudinal data are national-representative and randomly selected. The final sample interviewed in

[10]This assumption means that the errors made at two subsequent time periods are conditionally independent given the true states

2012 consists of 12060 households, which includes 6752 original households (out of 8371 interviewed in 2006, which followed itself 4816 households interviewed in 1998), 3308 split households and a refresher sample of 2000 households. The attrition cross-sectional and panel weights attributed in these data sets by Assaad and Krafft (2013) allow to expand sample figures to a macro population level.

We make use in this paper of the rich retrospective information available in both questionnaires as well as current state information and the newly added module (in ELMPS12) of life events' calendar. Unfortunately, the ELMPS 1998 round did not contain what we require as "full" (compared to ELMPS06 and ELMPS12) retrospective accounts about the interviewed individuals. The type and different characteristics of an individual's first state in the labor market have not been collected. We therefore choose to only use the cross-section stocks from this round in our analysis, for identification and comparability reasons in the correction model, given that it does not contain the minimal information required to extract the longitudinal retrospective panel data.

Following the methodology adopted by Yassin (2014), we extract two retrospective panel datasets for the periods 1999-2006 (from ELMPS06) and 1999-2012 (from ELMPS12). ELMPS06 records only the year of start of an individuals' state allowing us to just extract an annual panel data set between 1999-2006. The availability of the month and year of the date of start of a state in ELMPS12, on the other hand, enables the extraction of both semi-annual and annual transitions. Since missing values about the month and year of start of a state are problematic when creating such synthetic panels, we adopted the same assumptions made in Yassin (2014) to create the ELMPS12 panel datasets. Consequently, the cross-state transitions do not get evenly distributed over the 2 semesters of the year. Semi-annual transitions are not representative for a 6 months period. However as they are lumped into an annual trajectory, this allows us to capture the maximum range of transitions an individual went through during the year t. Cross-state labor market transitions such as job finding and job separations are therefore derived from the semi-annual constructed panel, but then lumped into annual transitions in order to be representative as well as comparable with the 1999-2006 panel extracted from the ELMPS06[11].

The general sample of the retrospective panel datasets includes individuals who answered the retrospective question i.e those who ever worked in the Egyptian labor market, the young unexperienced new entrants and the individuals who are permanently out of the labor force.

In this paper, we focus on employed, unemployed and inactive male individuals between 15 and 49 years of age. Our analysis exclude female workers since their movement in and out of the labor market most of the time follow personal motives such as marriage and child birth. Moreover, going back in time, our sample should have included people who were alive back then but passed away by the year of the survey i.e. 2006 and 2012 and hence did not respond to the ELMPS questionnaire. Due to this backward attrition, we were obliged to limit the age of our analysis group to what

[11] See Yassin (2014) for a detailed discussion of this procedure.

we refer to as the prime age group (i.e. between 15 and 49 years old). Another reason why one would want to avoid including old people within our analysis group is to limit recall error which is intuitively likely to increase with advanced age.

A potential type of error that our data is susceptible to face is the response error including the “present” mis-report bias and recall bias (Yassin, 2014). We cannot deal with the bias resulting from people deliberately mis-reporting their present employment status and information to avoid taxes and government registers. We therefore assume the non-existence of this bias. The extent of recall bias is examined and corrected by our constructed model in the next section.

In addition to the recall error, we also suspect the presence of what we call the “design” bias that leads to a systematic inaccuracy (in the same direction of the recall bias) in our constructed synthetic panels. The ELMPS survey contains very detailed (almost complete) questions about an individual’s current employment/unemployment/inactivity state. Questions about retrospective accounts are however minimal and very broad, where people mostly end up recording their jobs history ignoring histories about their unemployment spells. It’s also worth noting that individuals responding to the retrospective chapter in the survey are required to to have at least one work experience. Consequently, using the available collected data, we obtain correct estimate for current labor market state and increasingly biased estimates as we move backwards, especially among the unemployed and inactive who have never worked before. We examine in the next section the nature of the bias observed in the data and suggest a methodology to correct for it.

Finally, it’s important to note that in this paper we have two stages of analysis; one where an individual can occupy one of two states, namely employment (E) or unemployment (U). The transition from employment to unemployment is referred to as job separation and the transition from unemployment to employment is referred to as job finding. A three-state (Employment [E] - Unemployment [U] - Inactivity [I]) model is also developed where all inter- and intra- state transitions are illustrated and are used to calculate the job finding and separation rates of the three-state economy following Shimer (2012).

4 Recall and Design Bias

We first describe the link between worker flows and stocks data. Secondly, we present our method that corrects the data from the "recall and design bias". In the last part of this section, we present our “corrected” data.

4.1 Descriptive Statistics

Following Diamond-Mortensen-Pissarides (DMP) matching model of unemployment, in steady-state equilibrium, flows into unemployment (“separations”) equal flows from unemployment (“finds”). Using the flow balance equation, we therefore have

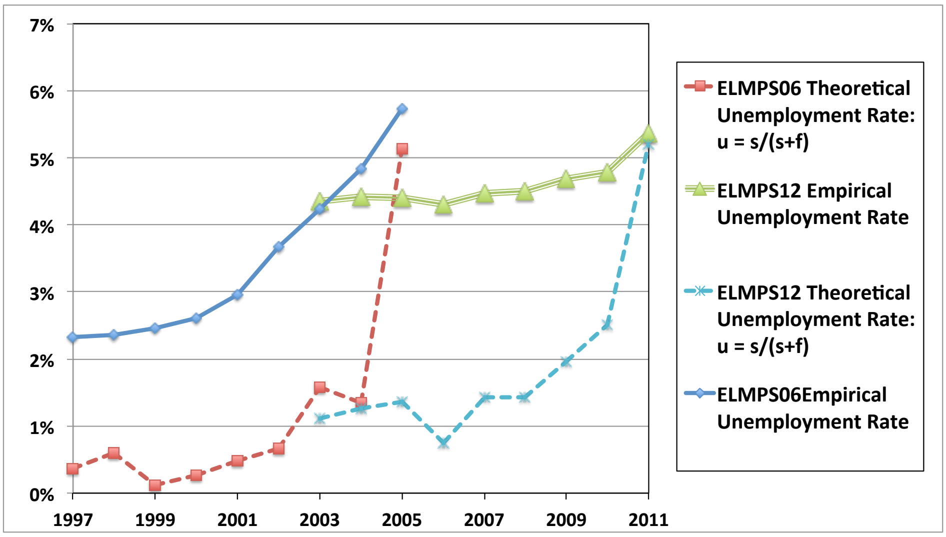
$$\underbrace{fU}_{\text{Probability to find a job} \times \text{no. of unemployed}} = \underbrace{sE}_{\text{Probability to quit/lose a job} \times \text{no. of employed}} \tag{1}$$

We can therefore show that in equilibrium, unemployment rate is

$$\underbrace{\frac{U}{L}}_{\text{Unemployment Rate}} = \frac{s}{s+f} \tag{2}$$

This represents the rate of unemployment to which the economy naturally gravitates in the long run. The natural rate of unemployment is determined by looking at the rate people are finding jobs, compared with the rate of job separation (i.e. People quitting either voluntarily or involuntarily in our case), and not the size of the population or the economy. In any given period, people are either employed or unemployed. As a result, the sum of structural and frictional unemployment [12] is referred to as the natural rate of unemployment also called "full employment" unemployment rate. This is the average level of unemployment that is expected to prevail in an economy and in the absence of cyclical unemployment. A healthy dynamic economy is therefore one with high separation and finding rates, keeping natural unemployment rate at its minimum.

Figure 1: Empirical Versus Theoretical Unemployment Rate, Male Workers between **15 and 49 years** of age



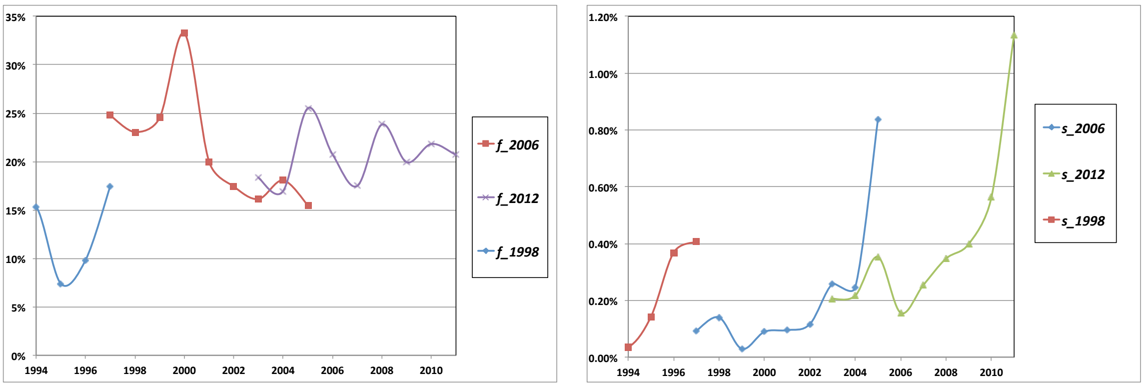
Source: LFSS surveys by CAPMAS and Authors' own calculations using ELMPS12.

[12] Frictional unemployment occurs naturally in any economy. People have to search to find an employer who needs their specific skills. Finding the right employee-employer match takes time and energy. Individuals have to look for the right job, and firms have to screen individuals for the right qualifications. This takes some time. Therefore, there will always be some level of unemployment in the healthiest of economies.

Using the job finding and job separation rates obtained from our constructed synthetic panel data sets, we plot in figure 1 the theoretical steady state versus the empirical unemployment (the rate of unemployed in the labor force). It is very obvious that the theoretical unemployment rate is correctly estimated and hence a good proxy for the prevailing unemployment rate in the economy only for the year 2011 i.e. the most recent year. The gap between the empirical and theoretical unemployment rate increases as we go back in time. As we examine the data thoroughly , we note that this gap can be mainly attributed to two factors acting in the same direction, namely to the recall error and the design nature of the ELMPS survey.

On the one hand, it is intuitive and very likely that when reporting their labor market histories, individuals would not recall their unemployment spells especially the short ones. On the other hand, as previously mentioned the design of our survey tends to under-record the unemployment and inactivity spells through the retrospective accounts. Consequently our estimations for the job separation rates over previous years are likely to be underestimated. On the other hand, people are more likely subject to over-recall and over-record their job finding transitions. This becomes clearly obvious as we overlap in figure 2 the job finding and separation rates from both panels, ELMPS06 and ELMPS12. Estimations for the job separation rates are increasingly being underestimated as we move backwards from the year of the survey, whilst job finding rates tend to be over-estimated. Even by adding the separation and job finding rates in 1998 obtained from the ELMPS98 synthetic panel which contains incomplete information, we still note the same trend in the bias.

Figure 2: Evolution of job finding and separation rates for workers between 15 and 49 years of age over the period 1999-2011 in Egypt, using ELMPS 2006 and ELMPS2012.

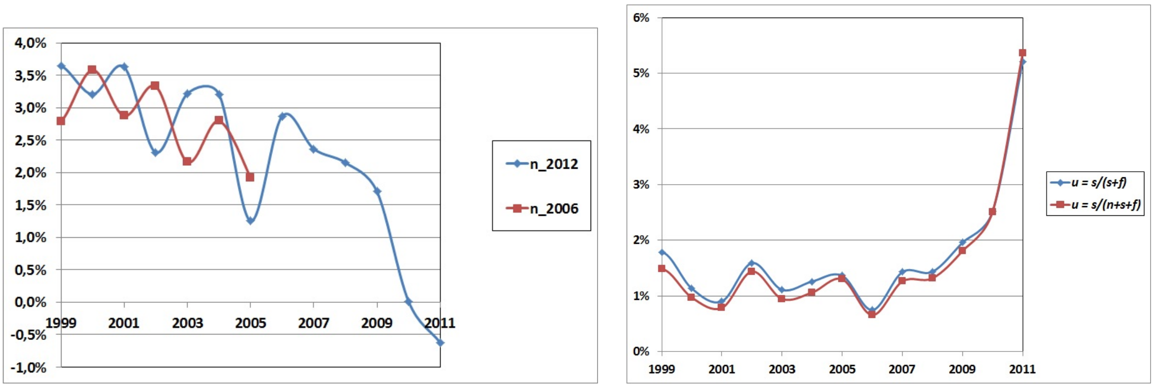


(a) Job Finding Rates (b) Job Separation Rates

Source:Authors' own calculations using ELMPS12 and ELMPS06.

A potential argument behind the reason of the backward increasing gap between the theoretical and empirical unemployment rates is the declining growth rate of the working age population in Egypt. The Steady State theoretical unemployment rate assumes a population that increases at a constant growth rate. We therefore replot in figure 3 the steady state theoretical unemployment rate with a declining population growth rate n. Even after correcting for the population dynamics, the theoretical unemployment rate curve keeps the same form confirming the backward increasing trend of the "recall and design" bias suggested above. For brevity and simplicity, we use throughout the rest of the paper the term recall error to refer to this combined bias.

Figure 3: Steady-State unemployment rates, with a constant versus decreasing population growth rate, male workers between 15 and 49 years of age.



(a) Working Age Population Growth (b) Steady-State Theoretical Unemployment Rate

Source: Authors' own calculations using ELMPS12 and ELMPS06.

4.2 A Model Correcting Recall Error

We present two models: the first one is a simple two-state model (here employment and unemployment), and the second is a three-state model (employment, unemployment and inactivity)[13].

4.2.1 A two-state model

We suppose that the true labor market histories are generated by a discrete-time Markov chain. The vector of the true labor market state occupied at year t is

$$X(t) = \begin{bmatrix} E(t) \\ U(t) \end{bmatrix} \tag{3}$$

where $E(t)$ and $U(t)$ represent the true proportion of employed and unemployed respectively in the labor force in year t. These are therefore the unbiased true moments of the population stocks

[13]The model can be easily extended to multiple state to be able to correct detailed labor market transitions, for instance among the different employment sectors and non-employment. However, given the nature of the data used and the available samples' sizes (Yassin, 2014), it is not possible to estimate a multiple-state model using the longitudinal retrospective panels extracted from the ELMPS surveys.

obtained from the data. The vector

$$x(t) = \begin{bmatrix} e(t) \\ u(t) \end{bmatrix} \tag{4}$$

denotes the observed empirical labor market state proportions at time t, with $e(t)$ and $u(t)$ being the observed proportion of employed and unemployed in the labor force in year t. These are the observed moments that decay,i.e. get biased due to the recall and design measurement errors as one goes back in time from the year of the survey.With $\lambda_{lk}(t-1,t)$ being the transition rates from state l occupied in $t-1$ to the state k occupied in t, the matrix

$$M(t-1,t) = \begin{bmatrix} \lambda_{EE}(t-1,t) & \lambda_{EU}(t-1,t) \\ \lambda_{UE}(t-1,t) & \lambda_{UU}(t-1,t) \end{bmatrix} {}^{14} \tag{5}$$

gives the observed transition probabilities between the year $t-1$ and the year t. These are obtained by aggregating the expanded number of individuals making the transition lk from the year $t-1$ to year t in the constructed retrospective panels and dividing by the stock of l in the year $t-1$. There exists a restriction on these transition rates: the sum of the elements of each column must be equal to one,

$$\begin{aligned} \lambda_{EU}(t-1,t) &= 1-\lambda_{EE}(t-1,t) && (6) \\ \lambda_{UE}(t-1,t) &= 1-\lambda_{UU}(t-1,t) && (7) \end{aligned}$$

The transition matrix in equation 5 leads to

$$x(t) = M'(t-1,t)x(t-1) \tag{8}$$

where $M'(t-1,t)$ is the transposed matrix of $M(t-1,t)$. The observed transition probabilities, as have been explained above, are biased due to recall and design measurement errors. To be able to correct this bias, an error term $\varphi_z(t-1,t)$, for $z = E,U$, is defined and associated to the z-type agents. These error terms vary in time and increase as one goes back in history, showing the loss of accuracy and memory as older events are being reported, as observed in the descriptive statistics in the previous section. The true matrix of transition probabilities between years $t-1$ and t can therefore be written as follows;

$$\begin{aligned} \Pi(t-1,t) &= \begin{bmatrix} \lambda_{EE}(t-1,t)-\varphi_E(t-1,t) & \lambda_{EU}(t-1,t)+\varphi_E(t-1,t) \\ \lambda_{UE}(t-1,t)+\varphi_U(t-1,t) & \lambda_{UU}(t-1,t)-\varphi_U(t-1,t) \end{bmatrix} \\ &= \begin{bmatrix} \lambda_{EE}(t-1,t)-\varphi_E(t-1,t) & 1-[\lambda_{EE}(t-1,t)-\varphi_E(t-1,t)] \\ 1-[\lambda_{UU}(t-1,t)-\varphi_U(t-1,t)] & \lambda_{UU}(t-1,t)-\varphi_U(t-1,t) \end{bmatrix} \end{aligned} \tag{9}$$

By correcting the observed transition matrix $M(t-1,t)$, in equation 5 and obtaining a true corrected one $\Pi(t-1,t)$, in equation 9, we obtain

$$X(t) = \Pi'(t-1,t)X(t-1) \tag{10}$$

where $\Pi'(t-1,t)$ is the transposed matrix of $\Pi(t-1,t)$. Given the shape of the recall bias observed and discussed in the previous section in figures 1 and 2, we assume that the error terms $\varphi_z(t-1,t)$, for $z = E, U$:

$$\varphi_z(t-1,t) \quad = \quad \nu_z(1 - \exp(-\theta_z(T-t))) \tag{11}$$

implying $\varphi_z(T-1,T) = 0$. As suggested by the descriptive statistics in the previous section, the worker flows are correctly estimated for the most recent year T, we therefore assume that $\Pi(T-1,T) = M(T-1,T)$ for a given retrospective panel data set. For the 2012 round of the ELMPS, for instance, the assumption $\Pi(2010, 2011) = M(2010, 2011)$ is made and for the ELMPS06 $\Pi(2004, 2005) = M(2004, 2005)$, reflecting that the most recent year of the retrospective panel extracted from a survey is the most accurate one. It's also important to note here that we exclude, from our analysis, transitions between the years 2011-2012 and 2005-2006, since these transitions are only observed for part of the year and not the entire years 2006 and 2012. The data collection process for both surveys was conducted early 2006 and 2012. Given the above setting and the availability of three waves from the ELMPS, we are able to estimate the parameters $\Theta = \{\theta_E, \theta_U, \nu_E, \nu_U\}$, using a Simulated Method of Moments (SMM). We solve the following system

$$\begin{aligned} g(x_T, \Theta) \quad &= \quad \left\{ \begin{bmatrix} X(2011)_{ELMPS12} \\ X(2005)_{ELMPS06} \\ \lambda_{EE}(2004, 2005)|_{2006} \\ \lambda_{UU}(2004, 2005)|_{2006} \end{bmatrix} - \begin{bmatrix} \widetilde{\Pi}_1(\Theta) \\ \widetilde{\Pi}_2(\Theta) \\ \widetilde{\Pi}_3(\Theta) \\ \widetilde{\Pi}_4(\Theta) \end{bmatrix} \right\} \\ &= \quad [\psi_T - \psi(\Theta)] \end{aligned} \tag{12}$$

where

$$\begin{aligned} \widetilde{\Pi}_1(\Theta) \quad &= \quad \left(\prod_{t=2006}^{2011} \Pi'(t-1,t) \right) X(2005)_{ELMPS06} \\ \widetilde{\Pi}_2(\Theta) \quad &= \quad \left(\prod_{t=1998}^{2011} \Pi'(t-1,t) \right) X(1997)_{ELMPS98} \\ \widetilde{\Pi}_3(\Theta) \quad &= \quad \lambda_{EE}(2004, 2005)|_{2012} - \nu_E(1 - \exp(-\theta_E(2011 - 2005))) \\ \widetilde{\Pi}_4(\Theta) \quad &= \quad \lambda_{UU}(2004, 2005)|_{2012} - \nu_U(1 - \exp(-\theta_U(2011 - 2005))) \end{aligned}$$

This set of restrictions lead to 4 identifying equations. The fist two line of $g(x_T, \Theta)$ are a 2×2

system with only one independent equation[15],

$$
\begin{aligned}
E(2011) &= \pi_{1,EE}E(2005) + (1-\pi_{1,UU})(1-E(2005)) \\
E(2005) &= \pi_{2,EE}E(1997) + (1-\pi_{2,UU})(1-E(1997))
\end{aligned}
$$

The two additional identifying restrictions are given by the 2×2 system leading to two independent restrictions:

$$
\begin{aligned}
& \begin{bmatrix} \lambda_{EE}(2004,2005) - \varphi_E(2004,2005) & \lambda_{EU}(2004,2005) + \varphi_E(2004,2005) \\ \lambda_{UE}(2004,2005) + \varphi_U(2004,2005) & \lambda_{UU}(2004,2005) - \varphi_U(2004,2005) \end{bmatrix}_{2012} \\
= & \begin{bmatrix} \lambda_{EE}(2004,2005) & \lambda_{EU}(2004,2005) \\ \lambda_{UE}(2004,2005) & \lambda_{UU}(2004,2005) \end{bmatrix}_{2006} \\
\Leftrightarrow & \left\{ \begin{aligned} \widetilde{\lambda}_{EE}(2004,2005) &= \lambda_{EE}(2004,2005) \\ \widetilde{\lambda}_{UU}(2004,2005) &= \lambda_{UU}(2004,2005) \end{aligned} \right.
\end{aligned}
$$

with

$$
\begin{aligned}
\varphi_E(2004,2005)|_{2012} &= \nu_E(1-\exp(-\theta_E(2011-2005))) \\
\varphi_U(2004,2005)|_{2012} &= \nu_U(1-\exp(-\theta_U(2011-2005))) \\
\varphi_E(2004,2005)|_{2006} &= 0 \\
\varphi_E(2004,2005)|_{2006} &= 0
\end{aligned}
$$

This gives only two restrictions because

$$
\begin{aligned}
& \begin{bmatrix} \widetilde{\lambda}_{EE}(2004,2005) & 1-\widetilde{\lambda}_{EE}(2004,2005) \\ 1-\widetilde{\lambda}_{UU}(2004,2005) & \widetilde{\lambda}_{UU}(2004,2005) \end{bmatrix}_{2012} \\
= & \begin{bmatrix} \lambda_{EE}(2004,2005) & 1-\lambda_{EE}(2004,2005) \\ 1-\lambda_{UU}(2004,2005) & \lambda_{UU}(2004,2005) \end{bmatrix}_{2006}
\end{aligned}
$$

where $\widetilde{\lambda}_{EE}(2004,2005) = \lambda_{EE}(2004,2005)\Big|_{2012} - \varphi_E(2004,2005)\Big|_{2012}$
and $\widetilde{\lambda}_{UU}(2004,2005) = \lambda_{UU}(2004,2005)\Big|_{2012} - \varphi_U(2004,2005)\Big|_{2012}$.
This model is therefore just identified with 4 free parameters and 4 restrictions. In order to be able

[15] These two first lines of $g(x_T, \Theta)$ are

$$
\begin{aligned}
E(2011) &= \pi_{1,EE}E(2005) + (1-\pi_{1,UU})(1-E(2005)) \\
1-E(2011) &= (1-\pi_{1,EE})E(2005) + \pi_{1,UU}(1-E(2005)) \\
E(2005) &= \pi_{2,EE}E(1997) + (1-\pi_{2,UU})(1-E(1997)) \\
1-E(2005) &= (1-\pi_{2,EE})E(1997) + \pi_{2,UU}(1-E(1998))
\end{aligned}
$$

where the two first lines lead to the same restriction, as the the two last lines.

to estimate $\Theta = \{\theta_E, \theta_U, \nu_E, \nu_U\}$, we solve J, where J is

$$J = \min_{\Theta}[\psi_T - \psi(\Theta)]W[\psi_T - \psi(\Theta)]' = g(x_T, \Theta)Wg(x_T, \Theta)' \tag{13}$$

Estimating the parameters θ_E, θ_U, ν_E and ν_U allows us to reproduce the true transition probabilities $\Pi(t-1,t)$ between the years 1999 and 2005 using the retrospective lingitudinal panel extracted from the ELMPS 2006 survey. Appendix 11 show the steps adopted to obtain the standard errors of the estimated parameters allowing us to construct confidence intervals around the corrected transition rates and steady state unemployment rate as well as test for their statistical significance.

4.2.2 Accounting for a large set of labor market transitions (N states)

The vector of the true labor market state occupied at year t becomes now

$$Y(t) = \begin{bmatrix} E(t) \\ U(t) \\ I(t) \end{bmatrix} \tag{14}$$

where $E(t)$, $U(t)$ and $I(t)$ represent the true unbiased moments of the proportion of employed, unemployed and inactive individuals respectively in year t. The vector

$$y(t) = \begin{bmatrix} e(t) \\ u(t) \\ i(t) \end{bmatrix} \tag{15}$$

denotes the observed labor market state histories at time t, with $e(t)$, $u(t)$ and $i(t)$ being the observed proportion of employed, unemployed and inactive in year t. With $\lambda_{lk}(t-1,t)$ being the transition rates from state l occupied in $t-1$ to the state k occupied in t, the matrix

$$N(t-1,t) = \begin{bmatrix} \lambda_{EE}(t-1,t) & \lambda_{EU}(t-1,t) & \lambda_{EI}(t-1,t) \\ \lambda_{UE}(t-1,t) & \lambda_{UU}(t-1,t) & \lambda_{UI}(t-1,t) \\ \lambda_{IE}(t-1,t) & \lambda_{IU}(t-1,t) & \lambda_{II}(t-1,t) \end{bmatrix} \tag{16}$$

gives the observed biased transition probabilities between the year $t-1$ and the year t. There exists a restriction on these transition rates: the sum of the elements of each column must be equal to one. Thus, we have:

$$\lambda_{EI}(t-1,t) \quad = \quad 1 - \lambda_{EU}(t-1,t) - \lambda_{EE}(t-1,t) \tag{17}$$

$$\lambda_{UI}(t-1,t) \quad = \quad 1 - \lambda_{UE}(t-1,t) - \lambda_{UU}(t-1,t) \tag{18}$$

$$\lambda_{IU}(t-1,t) \quad = \quad 1-\lambda_{IE}(t-1,t)-\lambda_{II}(t-1,t) \tag{19}$$

This transition matrix leads to

$$y(t) = N'(t-1,t)y(t-1) \tag{20}$$

As previously, the observation of the transition probabilities can be biased due to the recall error. To correct this bias, we propose to estimate, in this case, three functions, one for each subgroup. We define $\varphi_z(t-1,t)$, for $z = E, U, I$, as the associated error terms to the z-type agents (the subgroup). These errors also vary in time and increase as we go back in history. Again, these simply reflect that people tend to lose accuracy and memory as they report older events. This allows us to write the true matrix of transition probabilities between years $t-1$ and t as follows;

$$\Omega(t-1,t) = \begin{bmatrix} \lambda_{EE}-\varphi_E & \lambda_{EU}+a_1\varphi_E & \lambda_{EI}+(1-a_1)\varphi_E \\ \lambda_{UE}+b_1\varphi_U & \lambda_{UU}-\varphi_U & \lambda_{UI}+(1-b_1)\varphi_g \\ \lambda_{IE}+c_1\varphi_I & \lambda_{IU}+(1-c_1)\varphi_I & \lambda_{II}-\varphi_I \end{bmatrix}$$
$$\begin{bmatrix} \lambda_{EE}-\varphi_E & \lambda_{EU}+a_1\varphi_E & (1-\lambda_{EE}-\lambda_{EU})+(1-a_1)\varphi_E \\ \lambda_{UE}+b_1\varphi_U & \lambda_{UU}-\varphi_U & (1-\lambda_{UE}-\lambda_{UU})+(1-b_1)\varphi_U \\ \lambda_{IE}+c_1\varphi_I & (1-\lambda_{IE}-\lambda_{II})+(1-c_1)\varphi_I & \lambda_{II}-\varphi_I \end{bmatrix} \tag{21}$$

With the correction, we obtain

$$Y(t) = \Omega'(t-1,t)Y(t) \tag{22}$$

As in the two state model, the error terms $\varphi_z(t-1,t)$ are assumed to have the following functional forms:

$$\varphi_z(t-1,t) \quad = \quad \nu_z(1-exp(-\theta_z(T-t)))$$

implying $\varphi_z(T-1,T) = 0$. Since as we show in the previous section, our worker flows are correctly estimated for the most recent year T, we therefore assume that $\Omega(T-1,T) = N(T-1,T)$ for a given synthetic panel data set. This implies that for the ELMPS12 constructed panel $\Omega(2010,2011) = N(2010,2011)$ and for the ELMPS06 $\Omega(2004,2005) = N(2004,2005)$. Given this new three-state setting, we are now able to estimate the parameters

$$\Theta_3 = \{\theta_E, \theta_U, \theta_I, \nu_E, \nu_U, \nu_I, a_1, b_1, c_1\}$$

where $dim(\Theta_3) = 9$, by solving the following system

$$
\begin{aligned}
g(x_T, \Theta_3) &= \left\{ \begin{bmatrix} Y(2011)_{ELMPS12} \\ Y(2005)_{ELMPS06} \\ \lambda_{EE}(2004, 2005)|_{2006} \\ \lambda_{UU}(2004, 2005)|_{2006} \\ \lambda_{II}(2004, 2005)|_{2006} \\ \lambda_{EU}(2004, 2005)|_{2006} \\ \lambda_{UE}(2004, 2005)|_{2006} \\ \lambda_{IE}(2004, 2005)|_{2006} \end{bmatrix} - \begin{bmatrix} \widetilde{\Omega}_1(\Theta_3) \\ \widetilde{\Omega}_2(\Theta_3) \\ \widetilde{\Omega}_3(\Theta_3) \\ \widetilde{\Omega}_4(\Theta_3) \\ \widetilde{\Omega}_5(\Theta_3) \\ \widetilde{\Omega}_6(\Theta_3) \\ \widetilde{\Omega}_7(\Theta_3) \\ \widetilde{\Omega}_8(\Theta_3) \end{bmatrix} \right\} \\
&= [\psi_T - \psi(\Theta_3)] \qquad (23)
\end{aligned}
$$

where

$$
\begin{aligned}
\widetilde{\Omega}_1(\Theta_3) &= \left(\prod_{t=2006}^{2011} \Omega'(t-1, t) \right) Y(2005)_{ELMPS06} \\
\widetilde{\Omega}_2(\Theta_3) &= \left(\prod_{t=1998}^{2011} \Omega'(t-1, t) \right) Y(1997)_{ELMPS98} \\
\widetilde{\Omega}_3(\Theta_3) &= \lambda_{EE}(2004, 2005)|_{2012} - \nu_E(1 - \exp(-\theta_E(2011 - 2005))) \\
\widetilde{\Omega}_4(\Theta_3) &= \lambda_{UU}(2004, 2005)|_{2012} - \nu_U(1 - \exp(-\theta_U(2011 - 2005))) \\
\widetilde{\Omega}_5(\Theta_3) &= \lambda_{II}(2004, 2005)|_{2012} - \nu_I(1 - \exp(-\theta_I(2011 - 2005))) \\
\widetilde{\Omega}_6(\Theta_3) &= \lambda_{EU}(2004, 2005)|_{2012} - \nu_E(1 - \exp(-\theta_E(2011 - 2005))) \\
\widetilde{\Omega}_7(\Theta_3) &= \lambda_{UE}(2004, 2005)|_{2012} - \nu_U(1 - \exp(-\theta_U(2011 - 2005))) \\
\widetilde{\Omega}_8(\Theta_3) &= \lambda_{IE}(2004, 2005)|_{2012} - \nu_I(1 - \exp(-\theta_I(2011 - 2005)))
\end{aligned}
$$

Similar to the derivation done for the two state model, we therefore find out that the identification of Ω relies on restrictions laid out by equations that serve to guarantee the consistency of Ω with the evolution of stocks between 2005 and 2011 as well as 1997 and 2005. Since $1 = E + U + I$, these would yield 4 restrictions only allowing us to identify only four free parameters. We therefore add six more restrictions identified by

$$\Omega(2004, 2005)_{ELMPS06} = \Omega(2004, 2005)_{ELMPS12}$$

The relations between the transition rates in equations 17, 18 and 19 is the reason that we only yield six restrictions. Given the structure imposed by the three states model, we have ten restrictions and nine free parameters: the model is therefore over-identified. Further tests after estimation can therefore be developed in this case to test for its goodness of fit.

The same estimation methodology, as for the two-state model, is adopted where to estimate $\Theta =$

$\{\theta_E, \theta_U, \theta_I, \nu_E, \nu_U, \nu_I\}$, we solve J, where J is

$$J = \min_{\Theta_3}[\psi_T - \psi(\Theta_3)]W[\psi_T - \psi(\Theta_3)]' = g(x_T, \Theta_3)Wg(x_T, \Theta_3)' \tag{24}$$

We use our estimated $\hat{\theta}_z$, $\hat{\nu}_z$, $\hat{a}_1$, $\hat{b}_1$ and $\hat{c}_1$, for $z = E, U, I$, to reproduce the true transition probabilities $\Omega(t-1,t)$ between the years 1999 and 2005 using the retrospective panel extracted from the ELMPS 2006.

4.3 Empirical results: the "corrected" Data

Our estimations of the recall error terms allow us to obtain in table 1 the estimated results for $\hat{\phi}$, $\hat{\psi}$, $\hat{\psi}_E$, $\hat{\psi}_U$ and $\hat{\psi}_I$ for both models, namely E-U and E-U-I.

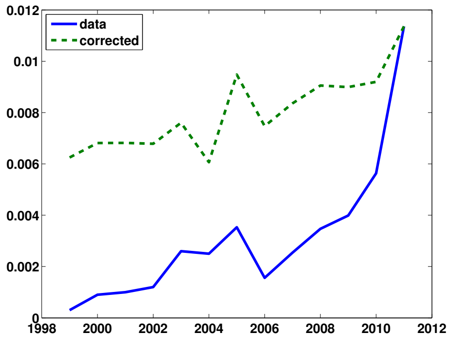
Table 1: Estimation of recall error terms

	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011
Model 1: E-U							
$\hat{\phi}$	0.006	0.0059	0.0058	0.0056	0.005	0.0036	0
$\hat{\psi}$	-0.1002	-0.0874	-0.0732	-0.0576	-0.0403	-0.0212	0
Model 2: E-U-I							
$\hat{\psi}_E$	0.0096	0.0096	0.0095	0.0093	0.0086	0.0065	0
$\hat{\psi}_U$	-0.071	-0.0602	-0.0489	-0.0373	-0.0253	-0.0129	0
$\hat{\psi}_I$	-0.0682	-0.0589	-0.0489	-0.0380	-0.0263	-0.0136	0

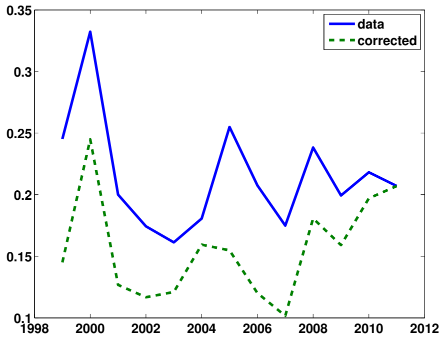
The corrected trends of the separation, job finding and three-state transition rates are hence obtained as follows in figures 4, 5 and 6. Indeed, as we have already shown in the descriptive time series obtained from overlapping the two surveys (ELMPS 2006 and ELMPS 2012), the separation is under-estimated and this bias is larger when the individual must appeal to distant memory. For the job finding rate, the transition rates are slightly over-estimated. The setting of our correction model succeeds in adjusting these trends to reflect as close as possible the prevailing labor market flows of the economy using the available data. These figures also show that the correction of the separation rates is more important than the one of the job finding rates. This was expected given the nature and extent of the recall as well as the design bias earlier discussed in the data section. As we compare our corrected separation and job finding rates in 1999 in figure 4, to the empirical rates we obtain from ELMPS98 in 1998 in figure 1, we find that our methodology allows us to obtain a very good proxy to the true level of these rates as we go backwards in time. Appendix 9 show the confidence intervals computed for the corrected separation and job finding rates in the two state model.

As we replot the steady-state unemployment rates using the corrected separation and job finding rates [16] for each of the two models, we obtain much more reasonable curves (figures 4c and 5c)[17]: our corrected theoretical unemployment rate share approximatively the same average of the aggregate empirical unemployment rate (obtained from stocks). Nevertheless, it seems more cyclical than the prevailing empirical unemployment rate, suggesting that it contains more information.

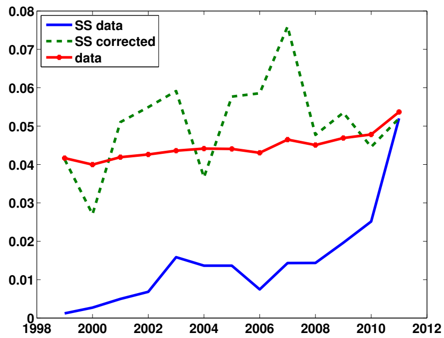
Figure 4: **Job finding, separation and unemployment Rates in Egypt for male workers between 15 and 49 years of age, corrected for recall bias, two-state employment/unemployment model**



(a) Employment to unemployment separation



(b) Unemployment to employment job finding



(c) Unemployment rate

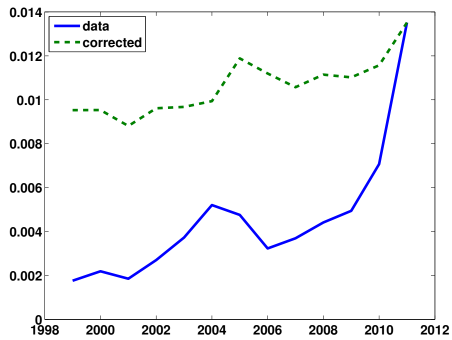
5 Policy Evaluation of the reform

In this section, our objective is to detect a structural break, linked to a permanent and unexpected change in the labor market policy. We first present our simple econometric methodology allowing

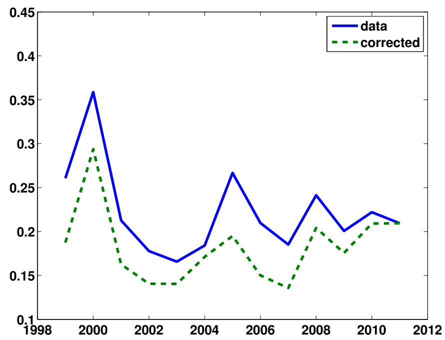
[16] Finding and Separation rates obtained in the three-state model are not of the same level as the rates in the two-state. This is pretty intuitive and normal since in the first model, an individual can only occupy one of two states (E or U), the transitions involved are therefore only EU and UE. In the three-state E,U,I model, the finding and separation rate take into consideration any other type of transition or state, an individual could have gone through before entering employment or exiting to unemployment. The probabilities calculated are therefore conditional on the existence of a third state in the labor market, namely inactivity and all related potential transitions.

[17] See appendix 9 for the confidence intervals of the steady state unemployment compared to the empirical stocks

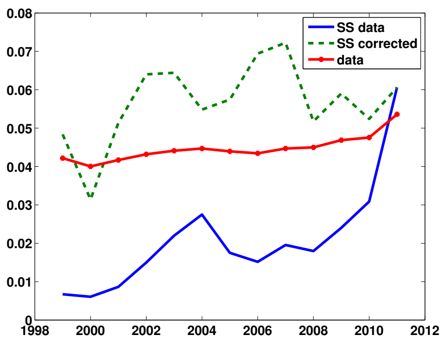
Figure 5: **Job finding, separation, unemployment rates in Egypt for male workers between 15 and 49 years of age, corrected for recall bias, three-state employment/unemployment/inactivity model**



(a) Separation



(b) Job finding



(c) Unemployment Rate

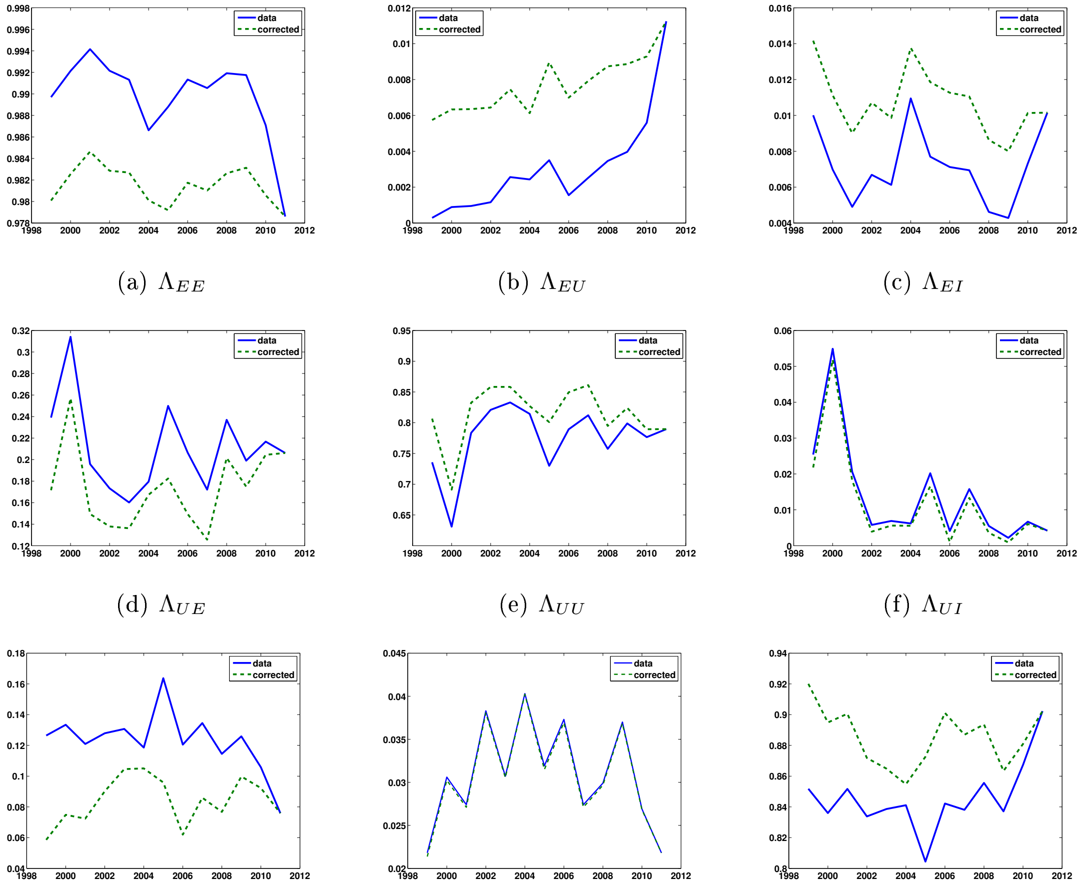
us to identify a permanent change linked to the reform, and then, we present and comment our empirical findings.

5.1 Econometric Methodology

A two-state labor market. In our time series, there are two components. The first one accounts for the business cycle, whereas the second accounts for long run component. Only this last part matters for our analysis. It is therefore necessary to purge the time series from their cyclical components. We extract the high frequency component of each series using the first difference of the observed output (in log): our final data are then the trend of the original time obtained after a projection on aggregate business cycle measures: we obtain a measure of the long run components of the worker flows. We test the robustness of your statistical approach by using the cyclical component of the output (in log) extracted by the Hodrick-Prescott (HP) filter instead to use the first difference of the output.

Any policy, that changes the natural rate of the worker flows ($x^{\star}$), introduces an instability on the

Figure 6: All transition rates in Egypt for male workers between 15 and 49 years of age, corrected for recall bias, three-state employment/unemployment/inactivity model



(a) Λ_{EE} (b) Λ_{EU} (c) Λ_{EI}

(d) Λ_{UE} (e) Λ_{UU} (f) Λ_{UI}

(g) Λ_{IE} (h) Λ_{IU} (i) Λ_{II}

relation

$$\widehat{x}_t = \widehat{b} + \mathbb{I}_a\widehat{\gamma} + \widehat{\epsilon}_t \quad \text{ for } x = f, s.$$

This allows us to test the impact of the 2003 reform in the Egyptian labor market. Without any observed policy change ($\widehat{\gamma} = 0$), the variations in $\widehat{x}_t$ are driven by unobservable changes in the matching and the separation processes. Remark that the time series $\widehat{x}^s_t$, built under the assumption of a stable relationship over time, can be interpreted as the counterfactual of an economy without any policy changes (this time series is build with $\widehat{\gamma} = 0$). If the policy change the natural rate of the worker flows, then the "true" series of the natural worker flows are given by $\widehat{x}_t$. The gap between $\widehat{x}_t$ and $\widehat{x}^s_t$ measures the impact of the reform.

Given that the unemployment rate is well approximated by its stationary value at the flow equilibrium, we can use our estimations of the natural flows to construct the implied natural unemployment. More formally, we have $u = \frac{s}{s+f}$. Thus, if we only focus on the component of the worker flows purged from the cyclical component linked to the GDP, we have $\widehat{u}_t = \frac{\widehat{s}_t}{\widehat{s}_t+\widehat{f}_t}$ and $\widehat{u}^s_t = \frac{\widehat{s}^s_t}{\widehat{s}^s_t+\widehat{f}^s_t}$.

Finally, in order to measure the relative contribution of the worker flows in the unemployment dynamics, one can compute $\widehat{u}_t^f = \frac{\widehat{s}_t}{\widehat{s}_t+\widehat{f}_t^s}$: this time series gives the unemployment dynamics if only the job finding rate is affected by the reform, or in other words, the contribution of the change in the job finding rate to the natural unemployment variation.

Extension: Entry and exit from the labor force. In a developing rigid labor market such as Egypt, flows to and from inactivity play an important role as a determinant of final labor market outcomes. Examining the gross flows of workers, between the three labor market states, employment (E), unemployment (U) and inactivity, becomes essential to portray as fully as possible the real story and the particular nature of the market.

In such case we adopt the same econometric methodology described above to measure the impact of the 2003 new labor law on the three-state labor market transitions. However, as mentioned previously, we now have a 3×3 matrix of the corrected transition probabilities, $\Omega(t-1,t)$. With $\Lambda_{ji}(t-1,t)$ being the corrected transition rates from state j occupied in $t-1$ to the state i occupied in t, we re-write $\Omega(t-1,t)$ as follows;

$$\Omega(t-1,t) = \begin{bmatrix} \Lambda_{EE} & \Lambda_{EU} & \Lambda_{EI} \\ \Lambda_{UE} & \Lambda_{UU} & \Lambda_{UI} \\ \Lambda_{IE} & \Lambda_{IU} & \Lambda_{II} \end{bmatrix}$$

This therefore extract the cyclical component of the workers flows using the first difference of the observed output (in log)[18], and we analyze the behavior of the "natural" rate of worker flows using the model

$$\widehat{x}_t = \widehat{b} + \mathbb{I}_a\widehat{\gamma} + \widehat{\epsilon}_t \quad \text{for } x = \Lambda_{EE}, \Lambda_{EU}, \Lambda_{EI}, \Lambda_{UE}, \Lambda_{UU}, \Lambda_{UI}, \Lambda_{IE}, \Lambda_{IU}, \Lambda_{II}.$$

This allows us to test if the policy changes the natural rate of the worker flows or not.

We then use our estimations of the natural flows to construct the implied natural unemployment. Following Shimer (2012), in a three-state E-U-I model, the number of employed, unemployed and inactive individuals are determined by the following equations;

$$E = k(\Lambda_{UI}\Lambda_{IE} + \Lambda_{IU}\Lambda_{UE} + \Lambda_{IE}\Lambda_{UE})$$

$$U = k(\Lambda_{EI}\Lambda_{IU} + \Lambda_{IE}\Lambda_{EU} + \Lambda_{IU}\Lambda_{EU})$$

$$I = k(\Lambda_{EU}\Lambda_{UI} + \Lambda_{UE}\Lambda_{EI} + \Lambda_{UI}\Lambda_{EI})$$

where k is a constant set so that E, U and I sum to the relevant population. The steady-state

[18] As previously, a robustness check is provided by the use of the HP filter instead of the first difference of the output.

unemployment rate ($u = \frac{s}{s+f}$) in a three-state labor market can therefore be written as

$$u = \frac{\Lambda_{EI}\Lambda_{IU} + \Lambda_{IE}\Lambda_{EU} + \Lambda_{IU}\Lambda_{EU}}{(\Lambda_{EI}\Lambda_{IU} + \Lambda_{IE}\Lambda_{EU} + \Lambda_{IU}\Lambda_{EU}) + (\Lambda_{UI}\Lambda_{IE} + \Lambda_{IU}\Lambda_{UE} + \Lambda_{IE}\Lambda_{UE})}$$

The relative contribution of the worker flows in the unemployment dynamics is then calculated. One can compute $\widehat{u}_t^f = \frac{\widehat{s}_t}{\widehat{s}_t + \widehat{f}_t^s}$, a time series that gives the unemployment dynamics if only job finding rate is affected by the reform given no change in the separation rates. In the three-state model (where individuals can also be inactive), the separation and job finding rates take into account all intermediate states/transitions, an individual could have gone through before exiting into unemployment or entering into employment. The hypothetical separation and job finding rates are therefore calculated as follows;

$$\widehat{s}_t = \overline{\Lambda}_{EI}\overline{\Lambda}_{IU} + \overline{\Lambda}_{IE}\overline{\Lambda}_{EU} + \overline{\Lambda}_{IU}\overline{\Lambda}_{EU}$$

$$\widehat{f}_t^s = \Lambda_{UI}\overline{\Lambda}_{IE} + \overline{\Lambda}_{IU}\Lambda_{UE} + \overline{\Lambda}_{IE}\Lambda_{UE}.$$

In other words, we show the unemployment dynamics if the three-state model separation rate followed the same dynamics as before the 2003 reform.

5.2 Estimation and Results

In this section, we show that correcting for the recall bias enables us, to investigate the "true" evolution of worker flows trends over the period 1998-2012 in our both models; E-U and E-U-I. To illustrate the interest of our approach, we propose, in a first "naive" estimation, the impact of the reform suing non-corrected data. In a second step, using the corrected data, we provide a more robust analysis. We are then able to link changes in the job finding and separation rates to the 2003 New Labor Law implemented in Egypt in 2004.

5.2.1 A Naive Econometric Model

In a naive econometric scenario, the above recall error would be neglected: the data used in this "naive" approach are the non-corrected data. The job finding and separation rates are purged from their business cycle component. In order to account for the increase of the recall bias, we also introduce a linear and a quadratic trend: this is the "naive" method which allows this simple econometric model to have stationary residuals, given the shape of the non-corrected time series of separation and job finding rates. We hence use the following econometric model:

$$\widehat{x}_t = \beta_1 t + \beta_2 t^2 + b + \mathbb{I}_a \gamma + \widehat{\epsilon}_t \quad \text{for } x = f, s$$

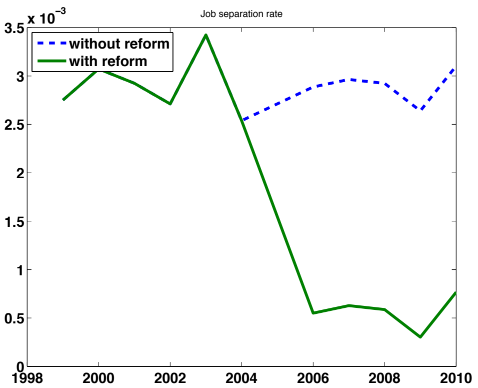
where f_t and s_t are respectively the observed job finding and job separation rates. β_1 and β_2 are two constants representing the linear and quadratic trends (in our case the increasing slope) of the time series. b is a constant term that encompasses the "true" constant and the structural rate of worker flows (hiring or separation). We also introduce a dummy $\mathbb{I}_a = 1$ after the reform and 0 before. By running such a regression, one obtains the following results reported in table 2.

Table 2: OLS regression results, a naive econometric model

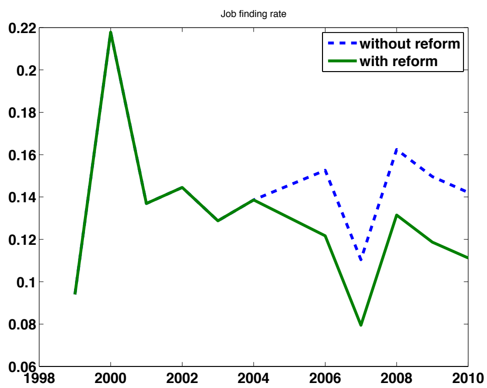
	f	f	s	s
β_1	-0.0360**	-0.0348	-0.000028	0.000214
β_2	0.0025*	0.0035	0.000042**	0.00044***
b	0.2534***	0.2253*	0.0017**	-0.0004
γ		-0.0310		-0.002337***

By neglecting the recall error, or more precisely, by using a reduced form analysis which does not use the restrictions provided by the data and the stock-flow models, the law seems to have reduced the unemployment rate. There has been a significant decrease in the separation rates and non-significant effect on the job finding rates. In such a case, the law seems inefficient in terms of flexibilizing the labor market, i.e. facilitating the hiring and firing process. Yet, the policy makers would be relieved seeing the unemployment rates reduced (see the section 6 for a figure of this unsatisfying correction of the unemployment rate). Unfortunately, the above naive scenario does not reflect not even part of the reality. By neglecting the structural interaction between the job finding and separation rates, and detrending each time series apart, one obtains misleading results: some data restrictions are not used in order to constraint the estimation. We show in the rest of the paper the impact of the reform after correcting for this recall bias given the underlying interaction between the structural stock-flow approach of the labor market model and the data.

Figure 7: Job Finding and Separation Rates with and without the new labor market reform in 2004, a naive econometric model



(a) Separation rate

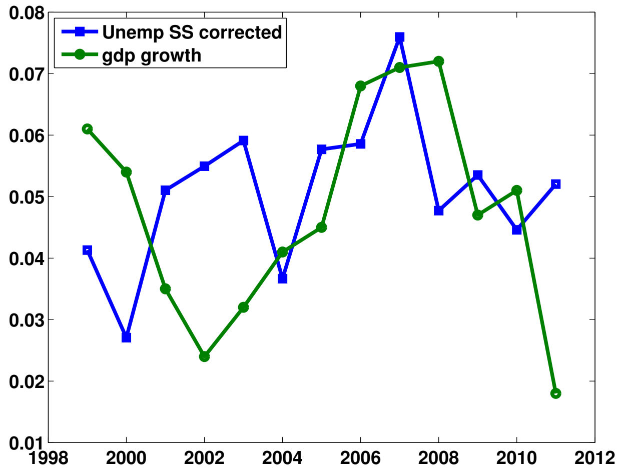


(b) Job finding rate

5.2.2 The evaluation of the reform with corrected data

After correcting the labor market flows from the recall error, we compute the steady-state unemployment rate ($u = \frac{s}{s+f}$), our proxy to the prevailing unemployment rate in the economy. Figure 8 shows the relationship between the GDP growth rate and the corrected steady-state unemployment rate in Egypt over the period 1999-2011. We note that before the year 2004, the year of implication of the new labor law, there has been a classical negative relationship between the unemployment rate and the GDP growth, which portrays an Okun's law relation between the unemployment and economic growth. However, after the reform this negative relationship gets distorted. We note a substantial increase in the unemployment rate accompanied by a rapid growth of GDP levels. In order to be able to explain such a paradox and because the reform can have different effects on job finding and separation rates, we decompose its impact by analyzing these two components of the unemployment rate.

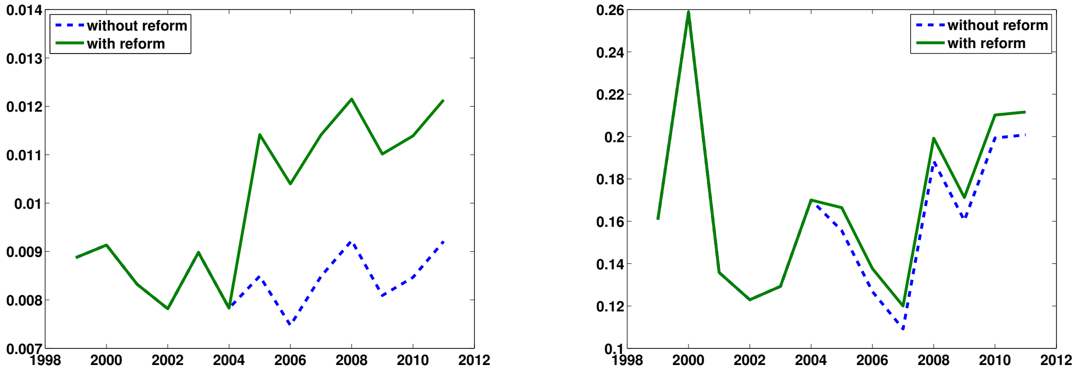
Figure 8: GDP growth rate and corrected steady-state unemployment rate in Egypt for male workers between 15 and 49 years of age



Our econometric methodology extracts the cyclical component from the trends of the labor market flows making it possible to detect a structural break observed in our time series showing the impact of the new labor law implemented in 2004. We first limit our analysis to individuals being either employed or unemployed. At first glance, figure 9 shows that the new labor law has lead to positive effects on both separation and job finding rates. Our regression results in 10, however, reveal that only the increase in separation rates was significant at the 1% level. With a very significant rise in the separations and a no significant change in the job findings, it becomes intuitive that the normal net effect of the reform explains the rise in the unemployment rates after 2004.

The full story of the Egyptian labor market is never however complete as one excludes flows entering and exiting the labor force. According to Yassin (2014), the new entrants (inactivity to employment) constitute a substantial flow of workers, that one can not ignore when analyzing the Egyptian labor

Figure 9: Trends of Job Finding and Separation Rates with and without the new labor market reform in 2004, a two-state E/U model



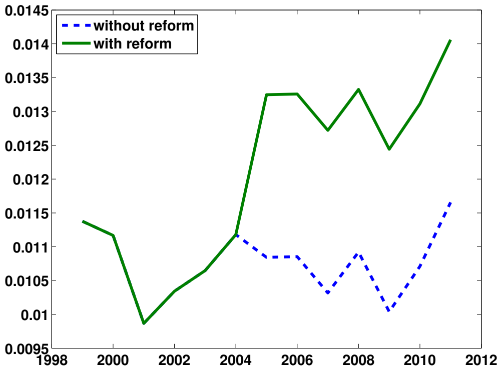
(a) E-to-U separation rate

(b) U-to-E job finding rate

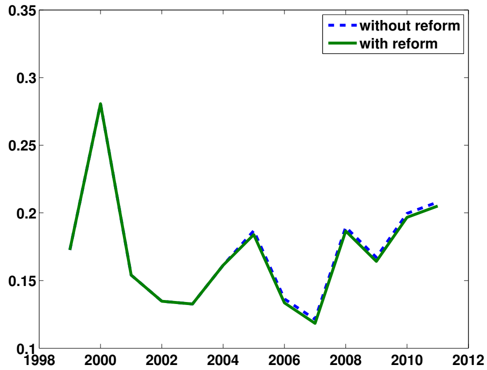
market. As a matter of fact it has been argued that, being a developing country, looking at participation rates might portray a better picture of the health of the labor market. Consequently, the detrended job finding and separation rates are reconstructed but this time for a three-state model where individuals can either be employed, unemployed or inactive. By modeling all possible labor market flows, we calculate separation and job finding rates, but this time accounting for the existence of the inactivity state. Our results are robust and coherent with the two-state E/U system. The 2003 reform lead to a significant increase in the separation rates and barely any impact on the job finding rates. Looking at the more detailed labor market transitions, we show that even though the structural break, observed in 2004, favored the unemployment-to-employment (Λ_{UE}) flows, as well as inactivity-to-employment (Λ_{IE}) labor market flows, the impact has been insignificant for both (The coefficients when ($\widehat{\gamma} \neq 0$) were insignificant for these flows.). The introduction of the dummy at the time of the reform neither improved the fit of the regressions for (Λ_{IE}) nor (Λ_{UE}). On the other hand, the coefficients of the dummy γ for the regressions of (Λ_{EI}) and (Λ_{EU}) were statistically significant (Table 5). It's important to note at this point that the E-to-I has been slightly affected negatively after the 2003 law. This impact was only significant at the 10% level and was mainly dominated by the very significant increment of the E-to-U flows. All regressions' estimations used in this section are illustrated in appendix 10. We also redo our regressions, by detrending our flows using the Hodrick and Prescott (1997) filter, in the appendix 10, showing that we obtain the same robust results.

In general, we note that the residuals of the regressions that omit the 2003 reform are non-stationary. For the significant cases (especially separations), the residuals become centered around zero when the reform is taken into account. This supports the significant impact of the dummy variable reported in the tables 3, 4 and 5.

Figure 10: Job Finding and Separation Rates with and without the new labor market reform in 2004, a three-state E-U-I model

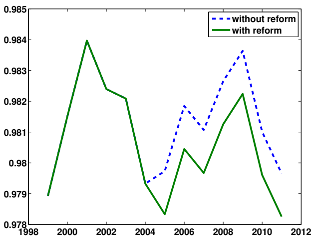


(a) Separation rate

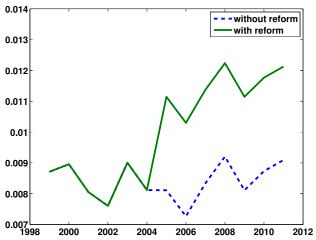


(b) Job finding rate

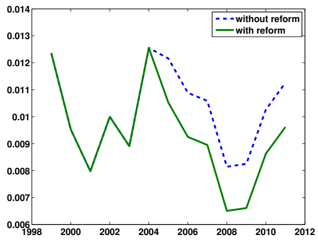
Figure 11: Trends of labor market transition rates with and without the new labor market reform in 2004, a three-state E-U-I model



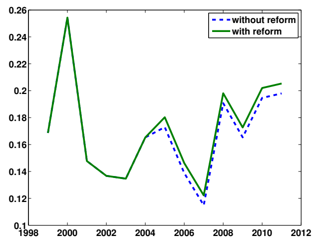
(a) Λ_{EE}



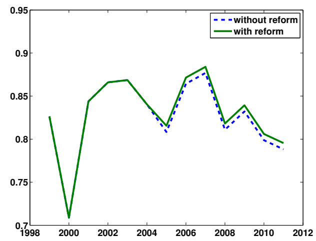
(b) Λ_{EU}



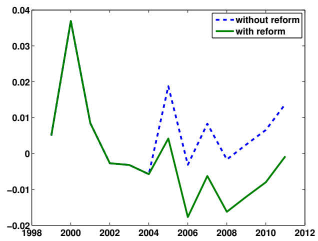
(c) Λ_{EI}



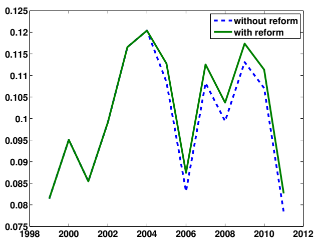
(d) Λ_{UE}



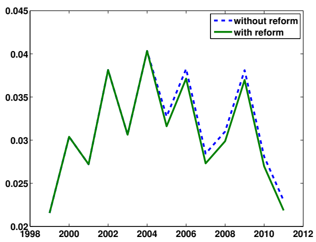
(e) Λ_{UU}



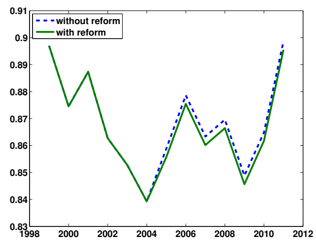
(f) Λ_{UI}



(g) Λ_{IE}



(h) Λ_{IU}

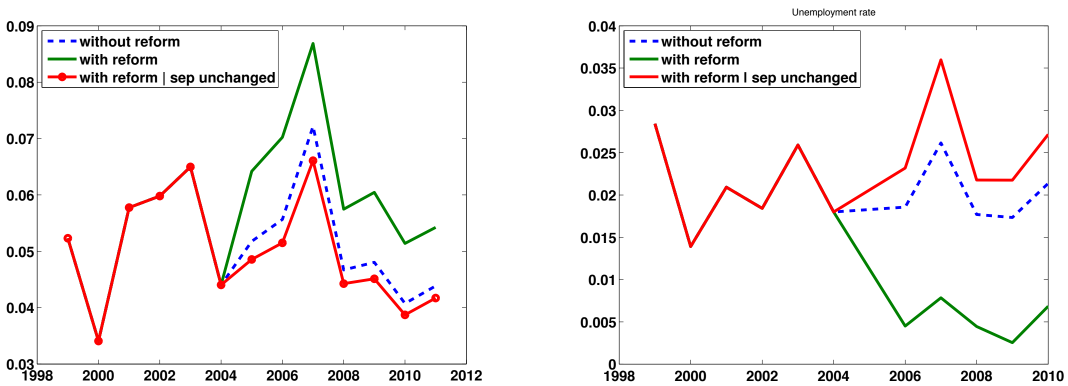


(i) Λ_{II}

6 Counterfactuals and Implications

Having shown the effects of the reform on labor market flows (the components of unemployment), we were able to deduce that the dynamics of the separation rates has a much more dominant impact, especially after the new 2003 labor law, on the variability of the unemployment rate than the job finding rates. Given that the policy reform is unexpected and that the labor market flows are jump variables, one can use our estimation results to decompose the unemployment dynamics between each of its components.

Figure 12: Counterfactual evolution of unemployment rate if separation rates followed the same dynamics before the labor market reform in 2004, a two-state E-U model



(a) Unemployment rate

(b) Naive unemployment rate

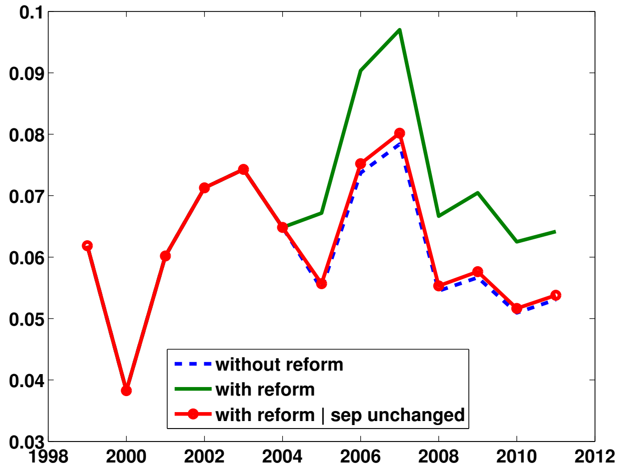
To be able to verify this observation and using the estimates of equations 38, 39, 42 and 43, we construct counterfactual experiments. After extracting the cyclical component of the worker flows driven by the output gap, and then focussing only on the structural changes on the labor market, we can construct two time series: the first where it is assumed that the reform has no impact on the structural worker flows ($\widehat{\gamma} = 0$) and the other where the estimates of the 2003 reform are take into account ($\widehat{\gamma} \neq 0$). We therefore plot the evolution of unemployment rate after the reform assuming the separation rates have followed the same dynamics before the law. In other words, these time series assume that the separation rates remain unaffected by the reform. This scenario captures the impact of the reform on the variability of the unemployment rate if and only if the law had an impact on the Egyptian labor market's job finding rates. We reproduce the same exercise with the "naive" econometric model presented in the section 5.2.1.[19] The two panels of figure 12 show that the use of the corrected data, that take into account the restrictions of the markovian processes of the workers flows, does not lead to the same predictions of a reduced form estimation. Our correction clearly matters, even for a policy evaluation.

Figures 12 and 13 show that, whether we take into consideration the existence of a third state of

[19] Given the non-stationarity of the uncorrected job flows data, the average of the job finding and separation rates are $x = \frac{1}{T}\sum_t(\beta_1 t + \beta_2 t^2) + b$.

inactivity in the market or not, the relative contribution of the separation rates to the Egyptian unemployment dynamics is substantial and significant. The structural increase in the unemployment rates after the reform is mainly due to the increase in separation rates. The positive responses (decrease in unemployment) due to the insignificant increase in the job finding rates were definitely outweighed by the significant impact of the augmented separations (figure 12). Adding inactivity as a third state in the economy, the positive impact of the job findings on the unemployment is no more observed (since job findings hardly changed in this model) and all the unemployment variations are attributed to the separations increase in this case. The Egyptian unemployment rate was therefore more responsive and had a larger elasticity vis-a-vis the variation in the level of the separation rate. It is true that it's important for an economy, in order to promote higher productivity levels associated with economic growth, to increase job destruction (i.e separations). This phenomenon should however be accompanied by new productive jobs being created in a much greater magnitude; in other words a more proportional increase in the job findings. This assures a healthy dynamic labor market with natural unemployment rates maintained at low levels. Generally, the law achieved only part of its double-sided mission, where the firing process was to some extent facilitated. Yet it has not been offset by a sufficiently increased and facilitated hiring. As a matter of fact, the law did not affect by any means the hiring process in the Egyptian labor market. In simple words, more jobs were being destructed, than before the law, while the same number of jobs were being created. A normal consequence would be a rise in the unemployment even if the economy has been experiencing rising rates of economic growth.

Figure 13: Counterfactual evolution of unemployment rate if separation rates followed the same dynamics before the labor market reform in 2004, a three-state E-U-I model



7 A theoretical attempt to evaluate the partial failure of the reform

In this section, we survey the conventional Mortensen and Pissarides (1994) theoretical model, showing the impact of a reduction of firing costs on the labor market's equilibrium. According to the model, the introduction of such reform, modelled as a decrease in the firing taxes, would lead to the increase of both separation and job finding rates. These theoretical predictions supports the liberalization of the labor market. Nevertheless, according to our empirical results, following the introduction of a more flexible employment protection policy in the market, only the job separations in Egypt increased while the job findings remain unchanged. We therefore try to explain this phenomenon using the theoretical model. We show that an increase in corruption can explain the partial failure of the reform.

7.1 Setting the Model

We set an equilibrium search model with a matching function $m(v, u)$ that characterizes the search and recruiting process by which new job-worker matches are created. The recruiting intensities across employers and workers are the same. The matching function is characterized by constant returns where $m(v, u) = m(1, \frac{u}{v})v \equiv q(\theta)v$ with $\theta = \frac{v}{u}$ being the market tightness. A vacant job is filled at a rate $q(\theta)$; this rate decreases in θ since $q(\theta) = m(1, \frac{1}{\theta})$. Consequently with increasing market tightness, the vacancy takes longer to be filled (duration of the vacancy $= \frac{1}{q(\theta)}$). A worker finds a job at a rate $\theta q(\theta)$, which increases with θ. It follows that with increased labor market tightness, a worker takes a shorter duration to find a job (duration of being unemployed $= \frac{1}{\theta q(\theta)}$).

An existing match is destroyed if the idiosyncratic productivity falls below a reservation threshold, an endogenous variable R. It therefore follows that the unemployment incidence (E→U) is given by $\lambda F(R)$. If R increases, extra jobs will fall below the productivity threshold and $\lambda F(R)$ increases. The expected duration of a job is $\frac{1}{\lambda F(R)}$.

At steady-state, we have $\dot{u} = \lambda F(R)(1 - u) - \theta q(\theta)u = 0$. Steady-state unemployment rate can therefore be expressed as follows: $u = \frac{\lambda F(R)}{\lambda F(R)+\theta q(\theta)} = \frac{s}{s+f}$. As θ increases, the steady state unemployment decreases. As the reservation product pR increases (p being a worker's skill), more separations take place and the steady state unemployment increases.

A firm incurs two types of costs and they both increase as the skill sophistication/level becomes higher: *(i)* a set-up cost: pC (these are sunk up costs once the match is formed), and (i) a recruiting cost cp.

An employer and a worker meet, they bargain and agree on an initial wage $w_0(p)$. The job is created, production occurs until they get a shock and that's when they renegotiate a wage $w(x, p)$. If x ever falls below the reservation product, that's when the job is destructed. The firm pays a firing cost pT (imposed by the employment protection regulation). This increases with the skill of the worker because it costs more to get rid of a skilled worker than a less skilled one.

Firm Values

The value of a continuing match to the employer

$$rJ(x) = px - w(x) + \lambda \int_R^1 [J(z) - J(x)]dF(z) + \lambda F(R)[V - pT - J(x)] \tag{25}$$

The asset pricing equation of the present value of an unfilled vacancy is :

$$rV = q(\theta)[J_0 - V - pC] - pc \tag{26}$$

Initial value of the match to the employer:

$$rJ_0 = p - w_0 + \lambda \int_R^1 [J(z) - J_0]dF(z) + \lambda F(R)[V - pT - J_0] \tag{27}$$

New vacancies are posted until the capital value of holding a vacancy is equal to zero. i.e. replace $V = 0$ in equation 26

$$J_0 = \frac{pc}{q(\theta)} + pC \tag{28}$$

This represents that , at the free-entry condition, the cost of recruiting and hiring a worker should be equal to the anticipated discounted profit the employer gets from the job.

Worker Values

The value of the worker for the initial and the continuing matches are:

$$rW_0 = w_0 + \lambda \int_R^1 [(W(z) - W_0]dF(z) + \lambda F(R)[U - W_0] \tag{29}$$

$$rW(x) = w(x) + \lambda \int_R^1 [(W(z) - W(x)]dF(z) + \lambda F(R)[U - W(x)] \tag{30}$$

Value of being unemployed:

$$rU = b + \theta q(\theta)[W_0 - U] \tag{31}$$

Wage Determination and Nash Bargaining

The threatpoint is looking for an alternative match partner. β is the worker's bargaining power and consequently $1-\beta$ is the employer's. For the initial and the continuing wages, we have:

$$w_0 = \text{argmax}\{[W_0 - U]^\beta [J_0 - pC - V]^{1-\beta}\} \quad w(x) = \text{argmax}\{[W(x) - U]^\beta [J(x) - V + pT]^{1-\beta}\}$$

Differentiating with respect to the wage (w_0 or $w(x)$) and equating the derivative to zero, for a surplus $S_0 = J_0 - V - pC + W_0 - U$ or $S(x) = J(x) - V + pT + W(x) - U$, we obtain:

$$\begin{aligned} W_0 - U = \beta S_0 \qquad &\text{and} \qquad J_0 - V + pT = (1-\beta)S_0 \\ W(x) - U = \beta S(x) \qquad &\text{and} \qquad J(x) - V + pT = (1-\beta)S(x) \end{aligned}$$

For the continuing wage, we will neither have the set-up costs nor the job creation subsidy, but we will have the firing tax (not in the initial value since this is a cost that does not exist if the match is not formed initially). Hence, the wage rules are[20]

$$\begin{aligned} w_0 &= (1-\beta)b + \beta p(1 + c\theta - (r+\lambda)C - \lambda T) \\ w(x) &= (1-\beta)b + \beta p(\theta c + x + rT) \end{aligned}$$

7.2 Equilibrium

The job creation condition

Substituting the wage equations into the initial and continuing match value equations, we obtain:[21]

$$(1-\beta)[\frac{(1-R)}{r+\lambda} - T - C] = \frac{c}{q(\theta)} \tag{32}$$

The job destruction condition

A firm destroys a job if it becomes more profitable to keep the job vacant i.e. $V > J(z) + pT$ and a worker prefers to stay unemployed if $U > W(z)$. The reservation productivity is therefore $R = max\{R_e, R_w\}$, with R_e being the reservation productivity of the employer and R_w being the reservation productivity of the worker. It therefore follows that the necessary and sufficient condition is $R = R_e = R_w \Rightarrow J(R) + W(R) = V - pT + U$. The separation rule should be jointly optimal that it maximizes the "total wealth" (Employer + worker).

Again, substituting the wage equation $w(x)$ into the asset value equation, then evaluating $((r+\lambda)J(x))$ at z and R, we are able to calculate $J(z) - J(R) = \frac{1-\beta}{r+\lambda}p(z-R)$. This enables us to obtain

[20] See the appendix 11 for the complete derivation of the wage equations.

[21] See the appendix 11 for the complete derivation of the job creation curve.

the job destruction curve as follows:

$$\frac{b}{p} - rT + \frac{\beta}{1-\beta}c\theta \quad = \quad R + \frac{\lambda}{r+\lambda}\int_R^1 (z-R)dF(z) = R + \frac{\lambda}{r+\lambda}\int_R^1 (1-F(z))dz \tag{33}$$

7.3 The impact of the New Labor Law 2004

Employment protection laws are translated in the theoretical model via the firing tax T. Since we are dealing with a developing country where corruption is a common phenomenon, we can also think of the set up costs C as a corruption fixed cost. With a probability μ the employer is forced to pay at the start of a job an amount κ to a corrupt agent and with a probability $1-\mu$ he pays nothing. To be able to measure the impact of the new Egypt labor law 2004 on the equilibrium pair (R^*, θ^*), the effect on R^* and θ^* is obtained by differentiating the equilibrium conditions.

For the job creation condition, we obtain

$$\frac{c}{1-\beta}d\theta = \frac{1}{r+\lambda}\frac{q^2(\theta)}{q'(\theta)}dR + \frac{q^2(\theta)}{q'(\theta)}(dT + dC) \tag{34}$$

and differentiating the job destruction condition, we get

$$\frac{db}{p} - rdT + \frac{\beta}{1-\beta}cd\theta \quad = \quad \frac{r+\lambda F(R)}{r+\lambda}dR \tag{35}$$

Rewriting equation 34 as follows, and introducing it in equation 35, we obtain

$$\begin{aligned} d\theta &= \frac{1-\beta}{c}\frac{1}{r+\lambda}\frac{q^2(\theta)}{q'(\theta)}dR + \frac{1-\beta}{c}\frac{q^2(\theta)}{q'(\theta)}(dT + dC) \\ \Rightarrow \frac{db}{p} + \underbrace{\beta\frac{q^2(\theta)}{q'(\theta)}}_{-}dC + \underbrace{\left[\beta\frac{q^2(\theta)}{q'(\theta)} - r\right]}_{-}dT &= \underbrace{\left[r+\lambda F(R) - \beta\frac{q^2(\theta)}{q'(\theta)}\right]}_{+}\frac{dR}{r+\lambda} \end{aligned}$$

This implies that the variation of θ at the equilibrium is given by

$$d\theta \quad = \quad \frac{1-\beta}{c}\frac{q^2(\theta)}{q'(\theta)}\left[\frac{\frac{1}{p}}{r+\lambda F(R) - \beta\frac{q^2(\theta)}{q'(\theta)}}db + \frac{r+\lambda F(R)}{r+\lambda F(R) - \beta\frac{q^2(\theta)}{q'(\theta)}}dC + \frac{\lambda F(R)}{r+\lambda F(R) - \beta\frac{q^2(\theta)}{q'(\theta)}}dT\right]$$

If $db = 0$, then the model reveals that C and T must change at the same time in order to observe a constant job finding rate, as in the data. Indeed, we have $d\theta = 0$, iff

$$dC \quad = \quad -\frac{\lambda F(R)}{r+\lambda F(R)}dT \tag{36}$$

In this case, the equation 35 is reduced to

$$-rdT = \frac{r+\lambda F(R)}{r+\lambda}dR$$

which shows that when $dT < 0$, we have $dR > 0$. Hence, the joint evolution of T and C can explain why we observe more separations but not more creations when liberalization reforms are introduced in the labor market, as it is always the case in the usual Mortensen and Pissarides model.[22] Remark that if $dC = 0$, whereas $db > 0$, it is not immediate, without parameter restrictions to obtain a increase in separations without any changes in the job finding rate.

The empirical results, discussed above, show that in response to the new Egypt labor law, there has been a substantial increase in separations and almost no change (or a very trivial increase) in the job creation. A simple way to explain this via the theoretical model is therefore by setting $dC \neq 0$, as in equation 36.

Even if the firing taxes are reduced ($dF < 0$), but the corruption costs increase ($dC > 0$), the positive effect on job creation can be attenuated or even totally nullified. Explaining this in real world terms, it is possible to say that employers might perceive this reform as a potential increase for their surplus. Nevertheless, at the same time, it is possible for the corrupt agent to capture this new surplus by increasing the set-up costs: separations then rise instantaneously but hiring decisions do not change.

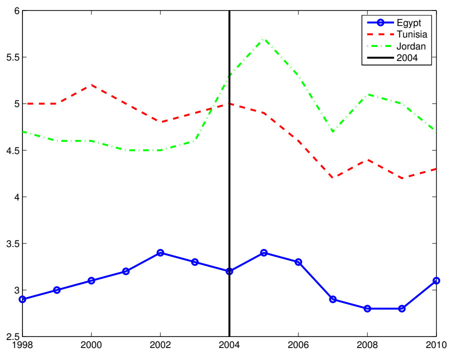
Is this explanation possible? It is not possible to measure corruption directly. Hence, our theoretical analysis can reveal the impact of the phenomenon on the labor market equilibrium. Corruption may be thought of as a form of rent seeking which adds a cost to transactions, in particular for new entrants or for the job creation. Do we observe an increase of corruption in Egypt at the time of the reform, or a change in the trend of perceived corruption at the time the new labor law came to action? If it is the case, then one can not reject our interpretation of our empirical results, based on the Mortensen and Pissarides model perturbed by changes in firing taxes (the labor market reform) and changes in corruption (installation/set-up costs). The Transparency International[23] provides a Corruption Perceptions Index (CPI) that allows to rank countries and territories based on how corrupt their public sector is perceived to be. It is a composite index constructed from a combination of polls and opinion surveys drawing on corruption-related data collected by a variety of reputable institutions. The CPI reflects the views of observers from around the world and residents of the

[22] If $db = dC = 0$, we have $\left[\beta\frac{q^2(\theta)}{q'(\theta)} - r\right]dT = \left[r+\lambda F(R) - \beta\frac{q^2(\theta)}{q'(\theta)}\right]\frac{dR}{r+\lambda}$ implying that $dT < 0$ leads to $dR > 0$, whereas the evolution of the job finding rate is driven by the evolution of θ, given by $d\theta = \frac{1-\beta}{c}\frac{q^2(\theta)}{q'(\theta)}\frac{\lambda F(R)}{r+\lambda F(R)-\beta\frac{q^2(\theta)}{q'(\theta)}}dT > 0$. Hence, in the classical Mortensen and Pissarides model, we have $d\theta > 0$ and $dR > 0$ when $dT < 0$. A more flexible employment protection reform, modelled as reduced firing taxes, would increase in this case, both job creations and destructions.

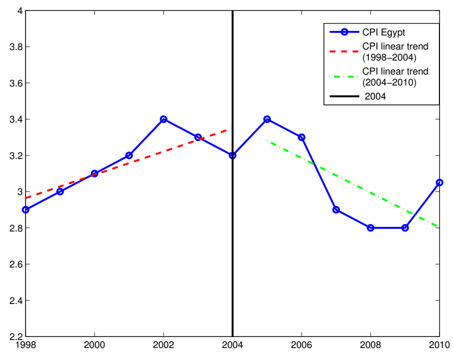
[23] Transparency International (TI) is a German INGO whose main purpose is to fight against corruption of governments and international governemental institutions. It was founded by Peter Eigen in 1993 and today has an international reputation, having autonomous sections in 80 countries all over the world (North as well as South).

surveyed countries. Using this index, countries are ranked according to a scale ranging from 0 to 10; 0 indicating high levels of perceived corruption and 10 indicating perceived corruption being very low. Figure 14 shows that according to the CPI, Egypt has known a significant increase in the perceived corruption after 2004. Before 2004, the corruption trend was perceived as declining (where the index has been increasing over time), this phenomenon was reversed after 2004 (CPI has declined significantly betwen 2004 and 2010)[24]. The figure 14 also shows that this phenomenon was not shared similarly by all the MENA region countries. In Tunisia, the perceived corruption increases significantly after 2004, however in Jordan, the levels of perceived of corruption have declined over that period.

Figure 14: Corruption Perceptions Index (CPI) as per Transparency International (TI) in Egypt, Tunisia and Jordan, over the period 1998-2010



(a) CPI in Egypt, Tunisia and Jordan



(b) Egypt's CPI linear trend before and after 2004

Another possible explanation to this might be the existence of informal and public employment sectors in addition to the private formal employer. The interaction and the flow of workers between these different employment sectors are not being considered by the aggregate Mortensen and Pissarides (1994) model. This expresses the need to extend the model to portray such developing countries' labor markets' nature where possible interactions and inter-sectoral transitions might take place with other employment sectors such as the private informal and public employers. Langot and Yassin (2015) describes such an extended theoretical model.

8 Conclusion

This paper addresses an important question namely the impact of labor market reforms that introduce flexibility in developing countries. We use the experiment of the implementation of the 2003 Egypt labor law on the dynamics of the Egyptian labor market, one of the most rigid markets at the

[24]Testing the linear time trend of Egypt's CPI before and after 2004 ($CPI = \beta * Time + \alpha$) yielded significant estimations of the coefficient β. Before the reform, $\hat{\beta} = 0.0643$ is significant at the 1% level and after 2004, $\hat{\beta} = -1.9322$ is significant at the 5% level

end of the nineties. This reform came to action in 2004, with the aim of enhancing the flexibility of the hiring and the firing processes. Given the two components of unemployment, separation and job finding rates, we measure the impact of the reform on each. Using constructed synthetic retrospective panel datasets from the Egypt labor market panel surveys 2006 and 2012, we are able to build a model to control for the recall and design bias such retrospective data sets are likely to encounter. We therefore obtain the corrected trends of separation and job finding rates over the period 1999-2011. These time series of workers' flows, that even official statistics fail to reproduce, are extremely important to be able to understand the behavior of the dynamics of the Egyptian labor market necessary for policy evaluation.

Our findings suggest that the new labor market reform increased significantly the separation rates and had no significant impact on the job finding rates. Having decomposed the impact of the new law on both components and also by using counterfactual experiments, we were able to conclude that the dynamics of the separation rates have had an increasing dominant role in accounting for the changes in the unemployment rate in Egypt especially after 2004. With increased separations and unchanged job findings, the unemployment rates in the Egyptian labor market were shifted upwards after 2004.

In the traditional Mortensen and Pissarides (1994) model, these empirical findings can be explained only if the liberalization of the labor market is accompanied by a capture of the new potential surpluses by corrupt agents. Indeed, in the Mortensen and Pissarides (1994) model, the decrease in the firing costs allows the entrepreneurs to take advantage of the facility to fire employees occupying obsolete jobs. But this decline of taxes also gives incentive to create new jobs: this last phenomenon is not observed in the data. Hence, we deduce that, expecting these increases in job surpluses, the corrupt agents capture the value of these new opportunities: the costs due to corruption will rise, and hence no hirings are encouraged. Knowing that the firms benefit from a larger job surplus, a corrupt agent is more likely to charge extra costs (corruption costs) from the firm than before the application of the reform. In addition to introducing hiring subsidies to commit himself, the policymaker needs to make sure that corruption and other set-up costs do not increase following such a reform. On the contrary, rules should be set to fight against corruption to decrease such costs for the firms.

From a policy evaluation point of view, the law achieved only part of its mission, where the firing (particularly to unemployment) process was largely facilitated. Yet it has not been offset by a sufficiently increased and facilitated hiring process.

Extensions: The correction methodology proposed in this paper assumes a specific parametric functional form of the estimated error terms. Further work is needed to expand on the role of this functional form and to test to what extent the obtained results depend on it. Moreover, since the three-state correction model is over-identified, given nine free parameters and ten identifying restrictions, we shall be able to develop tests of fit for the estimated error terms and hence the corrected transition matrices. Computing the standard errors of the estimated parameters in the three state model, would also enable us to test for their significance and construct confidence intervals for the corrected flows and theoretical steady state stocks as has already been done for the two state correction model. Calculating boot-strapped standard errors of both the two-state and three-state models is also considered for future work.

Appendix

9 Statistical Inference of the Correcting Parameters

9.1 Computing the Variance of Θ

In order to be able to test for the statistical significance of our correction methodology, we adopt the following steps to be able to calculate the standard deviations of the estimated matrix of the unknown parameters $\hat{\Theta}$. We have

$$\begin{aligned} g(x_T, \widehat{\Theta}) &= g(x_T, \Theta_0) + Dg(x_T, \Theta_0)(\widehat{\Theta} - \Theta_0) \\ \underbrace{Dg(x_T, \widehat{\Theta})' W g(x_T, \widehat{\Theta})}_{=0 \quad FOC} &= Dg(x_T, \widehat{\Theta})' W g(x_T, \Theta_0) + Dg(x_T, \widehat{\Theta})' W Dg(x_T, \Theta_0)(\widehat{\Theta} - \Theta_0) \end{aligned}$$

where the left hand side of this last equation is equal to zero because it corresponds the the FOC of the problem $\min_\Theta J$:

$$Dg(x_T, \widehat{\Theta})' W g(x_T, \widehat{\Theta}) = 0 \tag{37}$$

Hence, we deduce that

$$\sqrt{T}(\widehat{\Theta} - \Theta_0) = \left[Dg(x_T, \widehat{\Theta})' W Dg(x_T, \Theta_0)' \right]^{-1} Dg(x_T, \widehat{\Theta})' W \sqrt{T} g(x_T, \Theta_0)$$

Given that $Dg(x_T, \widehat{\Theta}) = -D\psi(\Theta_T)$, we have

$$\sqrt{T}(\widehat{\Theta} - \Theta_0) = \left[D\psi(\widehat{\Theta})' W D\psi(\Theta_0)' \right]^{-1} D\psi(\widehat{\Theta})' W \sqrt{T}[\psi_T - \psi(\Theta_T)]$$

If, asymptotically, $\sqrt{T}[\psi_T - \psi(\Theta_T)] \to \mathcal{N}(0, W^{-1})$, then

$$\sqrt{T}(\widehat{\Theta} - \Theta_0) \to \mathcal{N}(0, \Sigma_\Theta)$$

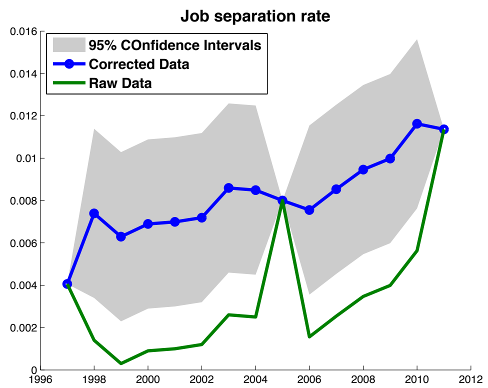
with

$$
\begin{aligned}
\Sigma_\Theta &= \left[D\psi(\widehat{\Theta})'WD\psi(\Theta_0)'\right]^{-1} D\psi(\widehat{\Theta})'WW^{-1}WD\psi(\widehat{\Theta})\left[D\psi(\widehat{\Theta})'WD\psi(\Theta_0)\right]^{-1} \\
&= \left[D\psi(\widehat{\Theta})'WD\psi(\Theta_0)'\right]^{-1}
\end{aligned}
$$

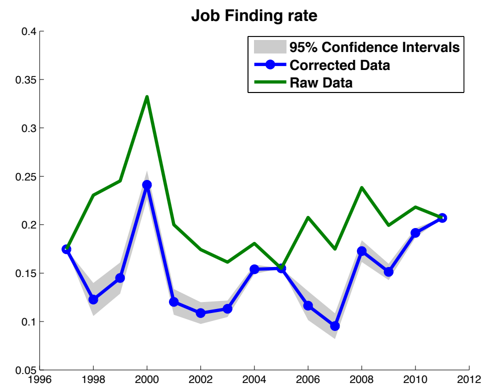
9.2 Corrected Flows and Steady-state Unemployment with Confidence Intervals

The proposed correction methodology produces sugnificant estimated parameters. In figure 15, we show the confidence intervals computed around the corrected time deries of the separation and job finding rates, as well as the theoretical steady state unemployment. The corrected flows are significantly different from the biased raw data flows and the corrected steady state unemployment rate is significantly not different from the empirical unemployment rate and can therefore be used as a proxy for the unemployment rate in Egypt over the period 1999-2011 in our analysis.

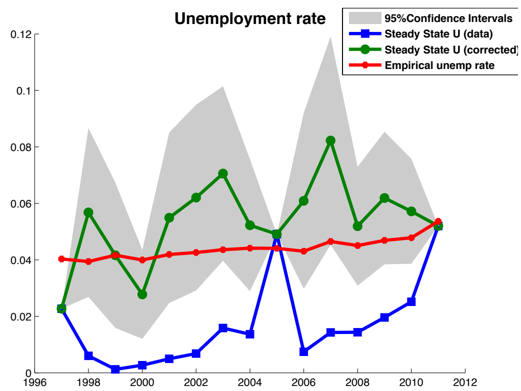
Figure 15: Job finding, separation and unemployment Rates in Egypt for male workers between 15 and 49 years of age, corrected for recall bias, two-state employment/unemployment model



(a) Employment to unemployment separation



(b) Unemployment to employment job finding



(c) Unemployment rate

10 OLS Regression Estimations

We report in the table 3 and 4 the ols regression estimations, of the two-state E-U model, for the equations 38 and 39 (where Δy_t is used as an approximation for the difference between the observed and the potential output), as well as the equations 40 and 41 (where y_t^{HP} is the detrended output series using the (Hodrick and Prescott, 1997) filter).

$$x_t = \alpha \Delta y_t + b + \epsilon_t \quad \text{for } x = f, s \tag{38}$$

$$x_t = \alpha \Delta y_t + b + \mathbb{I}_a \gamma + \epsilon_t \quad \text{for } x = f, s \tag{39}$$

$$x_t = \alpha y_t^{HP} + b + \epsilon_t \quad \text{for } x = f, s \tag{40}$$

$$x_t = \alpha y_t^{HP} + b + \mathbb{I}_a \gamma + \epsilon_t \quad \text{for } x = f, s \tag{41}$$

Table 3: OLS regression results, a two-state E-U model

	f	f	s	s
α	-0.1436	-0.2577	-0.0122	-0.0430***
b	0.1633***	0.1629***	0.0086***	0.0085***
γ		0.0108		0.0029***

Table 4: OLS regression results, a two-state E-U model (with HP filter)

	f	f	s	s
α	0.6980	0.6880	-0.0033	-0.0072
b	0.1564***	0.1532***	0.0080***	0.0067***
γ		0.0062		0.0024***

In table 5, the three-state E-U-I ols regression estimations for the following equations 42, 43, 44 and 45 are illustrated.

$$x_t = \alpha \Delta y_t + b + \epsilon_t \quad \text{for } x = s, f, \Lambda_{EE}, \Lambda_{EU}, \Lambda_{EI}, \Lambda_{UE}, \Lambda_{UU}, \Lambda_{UI}, \Lambda_{IE}, \Lambda_{IU}, \Lambda_{II} \tag{42}$$

$$x_t = \alpha \Delta y_t + b + \mathbb{I}_a \gamma + \epsilon_t \quad \text{for } x = s, f, \Lambda_{EE}, \Lambda_{EU}, \Lambda_{EI}, \Lambda_{UE}, \Lambda_{UU}, \Lambda_{UI}, \Lambda_{IE}, \Lambda_{IU}, \Lambda_{II} \tag{43}$$

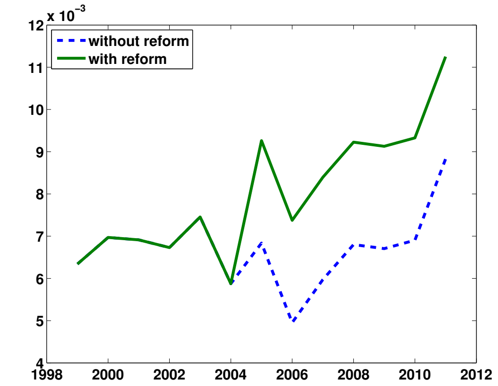
$$x_t = \alpha y_t^{HP} + b + \epsilon_t \quad \text{for } x = s, f, \Lambda_{EE}, \Lambda_{EU}, \Lambda_{EI}, \Lambda_{UE}, \Lambda_{UU}, \Lambda_{UI}, \Lambda_{IE}, \Lambda_{IU}, \Lambda_{II} \tag{44}$$

$$x_t = \alpha y_t^{HP} + b + \mathbb{I}_a \gamma + \epsilon_t \quad \text{for } x = s, f, \Lambda_{EE}, \Lambda_{EU}, \Lambda_{EI}, \Lambda_{UE}, \Lambda_{UU}, \Lambda_{UI}, \Lambda_{IE}, \Lambda_{IU}, \Lambda_{II} \tag{45}$$

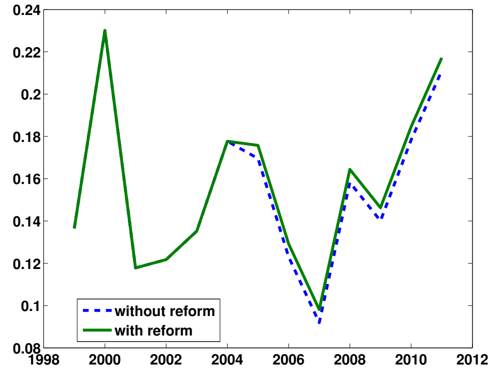
Table 5: OLS regression results, a three-state E-U-I model

	f	f	s	s		
α	-0.0570	0.2447	0.0020	-0.0302***		
b	0.1748***	0.1727***	0.0107***	0.0107***		
γ		-0.0029		0.0024***		
	Λ_{UE}	Λ_{UE}	Λ_{UU}	Λ_{UU}	Λ_{UI}	Λ_{UI}
α	0.1259	0.0485	-0.2484	-0.3243	0.1224	0.2758
b	0.1682***	0.1679***	0.8259***	0.8257***	0.0059	0.0064
γ		0.0074		0.0072		-0.0146*
	Λ_{EE}	Λ_{EE}	Λ_{EU}	Λ_{EU}	Λ_{EI}	Λ_{EI}
α	0.0043	0.0190	-0.0167	-0.0487***	0.0124	0.0296
b	0.9813***	0.9814***	0.0085***	0.0084***	0.0102***	0.0102***
γ		-0.0014		0.0030***		-0.0016*
	Λ_{IE}	Λ_{IE}	Λ_{IU}	Λ_{IU}	Λ_{II}	Λ_{II}
α	-0.3293	-0.3744	-0.0148	-0.0029	0.3441	0.3774
b	0.0998***	0.0997***	0.0313***	0.0314***	0.8688***	0.8690***
γ		0.0043		-0.0011		-0.0032
With HP filter	f	f	s	s		
α	0.8679	0.8712	-0.0149	-0.0183*		
b	0.1828***	0.1838***	0.0106***	0.0095***		
γ		-0.0020		0.0021***		

Figure 16: Trends of Job Finding and Separation Rates with and without the new labor market reform in 2004, a two-state E/U model, HP filter used to detrend the labor market flows

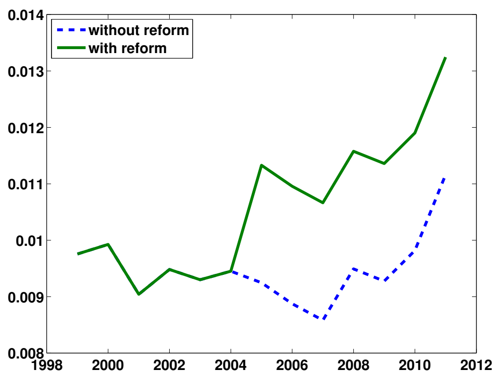


(a) Separation rate

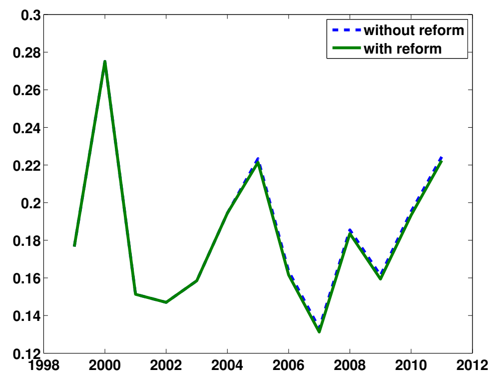


(b) Job finding rate

Figure 17: Trends of Job Finding and Separation Rates with and without the new labor market reform in 2004, a three-state E/U/I model, HP filter used to detrend the labor market flows



(a) Separation rate



(b) Job finding rate

11 Model

Adding equations 25 and 30, we obtain the following expression for the surplus $S(x)$:

$$S(x) = \frac{px + \lambda \int_R^1 S(z)dF(z) - r(V - pT + U)}{r + \lambda} \quad (46)$$

Since $S(R) = 0$, we have $\lambda \int_R^1 S(z)dF(z) = r(V - pT + U) - pR$. This implies that

$$S(x) = \frac{p(x - R)}{r + \lambda} \quad (47)$$

Now we go back to the $S(R)$:

$$\frac{pR + \lambda \int_R^1 S(z)dF(z) - r(V - pT + U)}{r + \lambda} = 0$$
$$\Leftrightarrow pR + \frac{\lambda p}{r + \lambda} \int_R^1 (z - R)dF(z) = r(V - pT + U)$$

The reservation product, pR, plus the option value of continuing the match attributable to the possibility that match product will increase in the future, the left-hand side, equals the flow value of continuation to the pair, the right-hand side of the equation.

Using the sharing rule, we obtain the following :

$$(1 - \beta)(\frac{(W(x) - U}{r + \lambda}) = \beta(\frac{J(x) - V + pT}{r + \lambda}) \tag{48}$$

The option value cancels out, and so we are left with:

$$w(x) = (1 - \beta)rU + \beta(px - r(V - pT))$$

For the initial surplus, we add equations 27 and 29, and we use $\lambda \int_R^1 S(z)dF(z) = r(V - pT + U) - pR$ to obtain:

$$(r + \lambda)S_0 \quad = \quad p(1 - R) - (r + \lambda)p(C + T) \tag{49}$$

We also know that $S(x) = \frac{p(x-R)}{r+\lambda}$ and for S_0, $x = 1$, we can therefore write:

$$(r + \lambda)S_0 \quad = \quad (r + \lambda)(S(x) - p(C + T))$$

To obtain w_0, we use the sharing rule:

$$\beta(J_0 - pC - V) = (1 - \beta)(W_0 - U)$$

The option value cancels and we finally obtain

$$w_0 = (1 - \beta)rU + \beta(p - r(V + U) - (r + \lambda)pC - \lambda pT \tag{50}$$

The free entry condition as mentioned previously is $J_0 = \frac{pc}{q(\theta)} + pC$ and so we can re-write it as $J_0 - pC = \frac{pc}{q(\theta)}$. With $V = 0$, the sharing rule is $J_0 - pC = (1 - \beta)S_0 \Rightarrow \frac{pc}{1-\beta} = q(\theta)S_0$.

The value of an unemployed worker is therefore re-written as linear in θ as follows:

$$rU \quad = \quad b + \beta\theta \frac{pc}{1 - \beta} \tag{51}$$

We substitute in the equations w_0 and $w(x)$, with $V = 0$:

$$\begin{aligned} w_0 &= (1-\beta)b + \beta p(1 + c\theta - (r+\lambda)C - \lambda T) \\ w(x) &= (1-\beta)b + \beta p(\theta c + x + rT) \end{aligned}$$

Subtituting the wage equations into the initial and continuing match value equations, we obtain:

$$(r+\lambda)J_0 = (1-\beta)p(1-x) + \beta p(r+\lambda)C + \beta(r+\lambda)pT - (r+\lambda)pT + (r+\lambda)(J(x) + pT)$$

Knowing that a job is destroyed when it's no more profitable to the employer, we can write $J(R) + pT = 0$. By evaluating equation 52 at R and since at free entry $J_0 = \frac{pc}{q(\theta)} + pC$, the job creation curve becomes:

$$(1-\beta)[\frac{(1-R)}{r+\lambda} - T - C] = \frac{c}{q(\theta)} \tag{52}$$

References

Assaad, R., and C. Krafft (2013): "The Egypt labor market panel survey: introducing the 2012 round," *IZA Journal of Labor & Development*, 2(1), 8.

Assaad, R., C. Krafft, and S. Yassin (2015): "Comparing Retrospective and Panel Data Collection Methods to Assess Labor Market Dynamics," .

Bassi, F., J. A. Hagenaars, M. A. Croon, and J. K. Vermunt (2000): "Estimating true changes when categorical panel data are affected by uncorrelated and correlated classification errors an application to unemployment data," *Sociological Methods & Research*, 29(2), 230–268.

Blanchard, O. J., and P. Diamond (1990): "The cyclical behavior of the gross flows of US workers," *Brookings Papers on Economic Activity*, pp. 85–155.

Campos, N. F., and J. B. Nugent (2012): "The dynamics of the regulation of labor in developing and developed countries since 1960," Discussion paper, IZA Discussion Paper Series.

Davis, S. J., and J. Haltiwanger (1990): "Gross job creation and destruction: Microeconomic evidence and macroeconomic implications," in *NBER Macroeconomics Annual 1990, Volume 5*, pp. 123–186. MIT Press.

——— (1992): "Gross job creation, gross job destruction and employment reallocation," *Quarterly Journal of Economics*, 107(3), 819–863.

De Nicola, F., and X. Giné (2014): "How accurate are recall data? Evidence from coastal India," *Journal of Development Economics*, 106, 52–65.

Hairault, J.-O., T. Le Barbanchon, and T. Sopraseuth (2013): “The cyclicality of the separation and job finding rates in France,” Discussion paper, Institute for the Study of Labor, IZA.

Hodrick, R. J., and E. C. Prescott (1997): “Postwar US business cycles: an empirical investigation,” *Journal of Money, credit, and Banking*, pp. 1–16.

Langot, F., and S. Yassin (2015): “Informal and Public Employment in developing countries: Theory and application to the Egyptian case,” .

Lollivier, S., and V. Daniel (2002): “Erreurs de mesure et entrées-sorties de pauvreté (Documents de travail sur le site web),” .

Lucas, R. E. (1976): “Econometric policy evaluation: A critique,” in *Carnegie-Rochester conference series on public policy*, vol. 1, pp. 19–46. Elsevier.

Magnac, T., and M. Visser (1999): “Transition models with measurement errors,” *Review of Economics and Statistics*, 81(3), 466–474.

Mortensen, D. T., and C. A. Pissarides (1994): “Job creation and job destruction in the theory of unemployment,” *The review of economic studies*, 61(3), 397–415.

Poterba, J. M., and L. H. Summers (1986): “Reporting errors and labor market dynamics,” *Econometrica: Journal of the Econometric Society*, pp. 1319–1338.

——— (1995): “Unemployment benefits and labor market transitions: A multinomial logit model with errors in classification,” *The Review of Economics and Statistics*, pp. 207–216.

Rendtel, U., R. Langeheine, and R. Berntsen (1998): “The estimation of poverty dynamics using different measurements of household income,” *Review of Income and Wealth*, 44(1), 81–98.

Shimer, R. (2005): “The cyclical behavior of equilibrium unemployment and vacancies,” *American economic review*, pp. 25–49.

——— (2012): “Reassessing the ins and outs of unemployment,” *Review of Economic Dynamics*, 15(2), 127–148.

Veganzones-Varoudakis, M.-A., and C. Pissarides (2007): *Labor markets and economic growth in the MENA region*, no. 278. Elsevier.

Wahba, J. (2009): “The impact of Labor market reforms on informality in Egypt: Gender and work in the MENA region,” Discussion paper, The Population Council Working Papers, 3. 0.

Wahba, J., and R. Assaad (2015): “Flexible Labor Regulations and Informality in Egypt,” Discussion paper, Economic Research Forum, Cairo.

WorldBank (2014): "More Jobs, Better Jobs: A Priority for Egypt," *World Bank Other Operational Studies*, 19993.

Yassin, S. (2014): "Job Accession, Separation and Mobility in the Egyptian Labor Market over the Past Decade," Discussion paper, Economic Research Forum, Cairo.