Measuring Labor Market Transitions in Europe: Identification and Validation Analysis

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Abstract

We consider the problem of measuring transition probabilities across employment, unemployment and nonparticipation when longitudinal data is not available and/or the available retrospective data is measured with error. We establish nonparametric point-identification conditions from time series of cross sections, focusing on the European Union Labor Force Survey (EULFS) microdata released by Eurostat, and assess their validity using auxiliary panel data for Portugal and the United Kingdom. We find that the variables in the EULFS do not satisfy the identification conditions. Consequently, we propose alternative data-releasing solutions allowing users to measure transitions from EULFS data while satisfying the existing legal requirements.

Keywords: Retrospective data; Measurement error; Labor force surveys.

JEL codes: C26; C52; E24; J21.

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1 Introduction

Transition probabilities across labor market states are routinely used to track the evolution of the labor market (secular trends, business cycles, etc.), and are an important input to develop, calibrate and assess models of the labor market (e.g. Krusell, Mukoyama, Rogerson and Şahin, 2017). Estimates of labor market transitions are usually based on panel data (e.g. Shimer, 2012 and Elsby, Hobijn and Şahin, 2015). However, in many countries either panel data are not available, are only available for the most recent decades or, if available, researchers’ access to them is complicated/impaired by administrative and legal constraints. An alternative is to use time series of cross sections (TSCS), which are usually easier to access, cover a longer time span, and often include retrospective information on past labor market state. But identification of transition probabilities with those type of data is challenging, since they lack individual longitudinal information. Indeed, we cannot find in the literature a statement of the nonparametric point-identifying conditions of transition matrices from TSCS that can facilitate an assessment of their plausibility and validity. The same can be said of retrospective information, since it usually suffers from measurement error.

This paper considers the problem of identifying and estimating transition probabilities across employment, unemployment and nonparticipation (or inactivity) using the International Labor Organization (ILO) classification of labor market states. Estimates of this transition matrix are of interest to both policy makers and researchers, since there is wide agreement about the importance of distinguishing nonemployed workers who are engaged in active search (the unemployed) from those who are not (the nonparticipants) when describing the state and evolution of the labor market (e.g. Elsby, Hobijn and Şahin, 2015). While our framework can be adapted to measure other forms of labor market mobility, we focus on estimates of the ILO transition matrix because the available data allows us to test the identifying assumptions. We seek to answer two questions. First, given existing TSCS with or without retrospective data, what is the exhaustive list of restrictions yielding nonparametric point-identification of the ILO transition probabilities? Second, are those restrictions valid in practice? We address both questions in the context of cross-country analysis of European labor markets using microdata from the European Union Labor Force Survey (EULFS), which is the largest and most comprehensive survey readily available to study European labor markets.
The EULFS records individual labor market states based on the ILO classification for 31 European countries, including all European Union (EU) members, and it is the European counterpart to the US Current Population Survey (CPS). The microdata is distributed to researchers as a TSCS for each country, even though all countries’ labor force surveys use rotating panels in the more recent years. For each individual in a cross section, we observe her current labor market state in the reference week based on the ILO definitions (hereafter ILO state), detailed information about her current labor market state (e.g. duration of unemployment) and individual characteristics (e.g. sex, age and education). For some countries (e.g. Denmark, France, Italy, Portugal, Spain and Sweden) we observe, in addition, retrospective information, namely individuals’ recalled subjective labor market state one year before the survey’s reference week (hereafter recalled state), as well as their current subjective labor market state.

Our first contribution is to provide a unified treatment of identification of ILO transition probabilities from TSCS with and without retrospective information. In both cases the identification strategy looks for a variable in the EULFS satisfying three conditions. First, the variable is observed for all individuals in any two consecutive cross-sectional samples. Second, it can be excluded from the conditional probability function defining the ILO transitions. Third, it is sufficiently correlated with the lagged ILO state. One can interpret this variable as an instrumental variable (IV) that solves a missing-data problem rather than the usual endogeneity problem. The IV should satisfy simultaneously an exclusion and a rank restriction. The exclusion restriction requires that, after conditioning on past ILO state, the instrument does not predict contemporaneous ILO state. The rank condition requires that the instrument predicts lagged ILO state. A generalization of this approach weakens the identification conditions further by stating them conditional on covariates (e.g. age, sex, education, etc.). When retrospective information is available, the subjective labor market state variables (recalled and contemporaneous) are a natural candidate IV. But an additional strategy is available, namely to interpret the recalled state as an error-ridden measurement of the lagged ILO state. We discuss conditions on different types of measurement error in the recalled state variable that are consistent with point-identification of the ILO transition probabilities.

Our second contribution is to assess the validity of the identification strategy above using the panel version of the EULFS for two countries, the United Kingdom (UK) and Portugal. The
EULFS data for the UK does not include retrospective information, but it does for Portugal. We conduct two validation exercises. The first exercise compares ILO transition probability estimates based on EULFS TSCS data and the corresponding validation panel data. The panel data results for the UK and Portugal show that TSCS estimates are far from longitudinal estimates. Perhaps surprisingly, we find that TSCS estimates using recalled state as an IV are further way from the longitudinal ones compared to the estimator that assumes that the recalled state is ridden with rather restrictive forms of measurement error. A distinctive feature of our validation exercise is the estimation approach we use for TSCS data. We use an estimator imposing non-negativity and additivity restrictions (the latter impose that probability estimates are consistent with the sample proportions in each ILO state in all periods) that are necessarily satisfied by the ILO transition matrix. The estimator is the minimizer of a strictly convex optimization problem with a unique solution, which simplifies the computations. That feature is especially important for our validation exercise, since it allows us to interpret our TSCS estimates as an implication of the exclusion restrictions. That would not be necessarily the case if we were using other methods, where problems with numerical convergence and multiple maxima could thwart that interpretation.

The second validation exercise uses panel data to test the exclusion restriction for alternative candidate IV. We estimate multinomial logit models where the included variables comprise the lagged ILO state, the candidate IV and a list of control variables. Using either UK or Portuguese data, we find that the exclusion restrictions are strongly rejected by the data. Lastly, we document the extent of measurement error in the recalled state using Portuguese data. That variable is potentially misclassified (individuals’ subjective reported state is likely to differ from the ILO classification) and exposed to recall error (individuals’ recall of past events are exposed to memory biases). In line with the literature measuring labor market transitions using labor force survey data (e.g. Bound, Brown and Mathiowetz, 2001, Jürges, 2007 and Hairault, Le Barbanchon and Sopraseuth, 2015), we find evidence of classification and recall errors. Moreover, we show that the form of those errors in the recalled state does not satisfy the exclusion restriction necessary to obtain point identification.

We draw two main implications from our analysis and results. First, despite our results showing that TSCS data are insufficient to produce reliable estimates of ILO transition prob-
abilities using EULFS data, we think the negative results using retrospective information are surprising and likely specific to the retrospective information in the EULFS. Our paper offers a new identification, estimation and validation framework that is not specific to either the EULFS or the measurement of transition probabilities across labor market states, and we hope it will be used by researchers in other contexts. Second, in light of the negative validation results, we suggest three strategies to make progress on the measurement of ILO transition probabilities in European countries using the EULFS. The first strategy is for Eurostat to release the panel version of the microdata. As far as we know, this strategy is not feasible as long as the existing legislation remains in place. A variation of this strategy entails collecting and harmonizing each member states’ panel data, in the cases where the latter is available. Even in those cases, it is a costly approach to be undertaken by single or teams of researchers.\footnote{First, some countries’ statistical offices (e.g. Portugal and the UK), restrict access to their panel microdata only to national accredited researchers. Second, the documentation necessary to use panel data is often only available in the countries’ official languages. Third, older panel data is typically not digitized (e.g. Denmark).} Despite these hurdles, Donovan, Lu and Schoellman (2020) have recently made extraordinary progress by collecting and harmonizing panel data for several European countries.\footnote{We see our paper as complementary to theirs, insofar as we document that the avenue they pursue is the most reliable one given the data made available by Eurostat. One drawback of their strategy is that the underlying microdata remain confidential, which prevents other researchers from pursuing alternative measurement approaches.} The second strategy is for Eurostat to release in each cross section the lagged ILO state as a variable without any additional longitudinal information. If that is not possible due to privacy restrictions, a third strategy would be for Eurostat to release an artificially-generated variable satisfying the conditions spelled out in this paper and that are sufficient to point-identify the ILO transition probabilities. Such a variable would limit violations to the privacy of respondents, while allowing researchers to measure labor market transition probabilities accurately.

**Related literature.** This paper contributes to the literature measuring labor market transition probabilities. That literature proposes and pursues different strategies to measure and identify transition probabilities in face of the challenges posed by specific datasets. For recent examples in the European context see Donovan, Lu and Schoellman, 2020, Elsby, Hobijn and Şahin, 2013 and Engbom, 2020 who use, respectively panel, and TSCS with retrospective labor market state and unemployment duration data. To our knowledge, ours is the first paper to consider the measurement of ILO transition probabilities using TSCS data with and without
Our paper is also related to the literature addressing measurement error in reported ILO state in panel data labor force surveys (e.g. Poterba and Summers, 1986, Magnac and Visser, 1999, Feng and Hu, 2013 and Shibata, 2019). In this paper, we aim to measure transition probabilities when individuals’ past ILO state is not observed (a missing-data problem), whereas that measurement-error literature aims to measure ILO transition probabilities allowing for reporting error (a measurement-error problem). While these two problems are clearly distinct, one can cast the point-identification problem for the retrospective information case as a measurement-error problem, where the recalled state is taken as an error-ridden measurement of the past ILO state. To complement our analysis, we discuss the restrictions imposed by our identification approach using the language of the measurement-error literature.

Organization. The rest of the paper is organized as follows. The next section presents the EULFS and states the problem of using it to measure ILO transition probabilities. Section 3 proposes restrictions to point-identify ILO transitions with TSCS, and assesses their validity using the UK Labor Force Survey as a validation dataset. Section 4 proposes two sets of alternative restrictions to point-identify ILO transitions based on TSCS with retrospective information on past labor market state, and assesses their validity using the Portuguese Labor Force Survey as a validation dataset. Section 5 concludes.

2 The Measurement problem

We want to measure ILO transition probabilities for the largest set of European countries and over the longest possible time period. This problem can be divided into two. The first concerns the choice of data source used to perform cross-country analysis of labor market dynamics in Europe. The second concerns the measurement of transition probabilities with the chosen data source. This section starts by presenting our chosen data source (the EULFS), and then compares it to alternative data sources on European labor markets. Next, it formalizes the problem of point-identifying ILO transition probabilities using EULFS data.

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3Elbry, Hobijn and Sahin (2013) use TSCS data to estimate transitions out of and into unemployment by combining data on stocks of unemployed workers at different durations.
2.1 The EULFS and alternative data sources on European countries

The EULFS started in 1960 covering the six initial EU member states. Since then, it has grown to cover virtually all European countries. The survey and its design suffered several changes over time, but starting in the early 1990s most countries adopted a common framework, including quarterly frequency and a rotating panel structure. The EULFS is produced by Eurostat in collaboration with member-state’s statistical offices. Each country is responsible for designing and implementing the survey according to European regulations, while Eurostat processes the data produced by member-states and distributes the harmonized microdata to researchers. In practice, the EULFS is a by-product of member-states’ national labor force surveys, which are in most countries the main statistical instrument to track the evolution of the labor market, especially the unemployment rate according to the ILO definition. While the current survey design of all national labor force surveys includes a rotating panel, due to legal reasons the EULFS microdata does not include individual longitudinal identifiers.\(^4\)

While there are other data sources on European labor markets, we focus on the EULFS microdata for three main reasons. First, the EULFS uses the ILO classification of labor market states. The ILO classification considers an individual unemployed if she is not working and jobless, seeking and available to start work (see Figure 6 of the Appendix for an illustration of the ILO classification). This definition offers an empirical counterpart to the concept of unemployment featured in search theory, which is the modern paradigm to understand aggregate labor markets. This stands in contrast to the measure of unemployment produced by administrative datasets, which classify as unemployed individuals who are claiming unemployment benefits. Moreover, the ILO classification is used in virtually all labor force surveys of the world, which facilitates international comparisons.

Second, for the purposes of measuring ILO transitions in European countries, the EULFS is the largest representative survey covering the longest time period. The European Community Household Survey (1994-2001) and its successor, the European Union Statistics on Income and Living Conditions (2003-), are two additional sources of cross-country panel data made available by Eurostat. They can be used to compute annual transition probabilities based on the ILO

\(^4\)According to Eurostat, 2019 ‘the anonymised LFS microdata (...) do not yet contain the information which would allow tracking people across waves: the household numbers are randomized per dataset. This was agreed with Member States and might be revised in the future’ (p.68).
classifications, but their small sample size and lower frequency limits the scope of the analysis. A comparison with US data sources may prove useful. The EULFS design was built on that of the US CPS, which is used in most US studies of labor market dynamics, since it combines a much larger sample and a rotating panel structure with very high measurement frequency (monthly).

Third, we focus on obtaining estimates from EULFS micro, instead of aggregate, data. This has two benefits. First, the EULFS microdata is readily available to researchers worldwide, which is important to guarantee that ours as well as others results can be verified, challenged, and improved by the research community. Second, it allows us to obtain estimates of the ILO transition matrix for subgroups of the population. Recently, Eurostat started publishing on its webpage experimental estimates of ILO transition probabilities since 2010 for some countries. Other than the very short time dimension, those estimates are provided at a rather aggregate level, which may limit the scope of the analysis (e.g. one cannot compute transition probabilities for married prime-age men). An alternative source of publicly-available data used to estimate aggregate ILO transitions across employment and unemployment in European countries is the OECD’s (Organization for Economic Cooperation and Development) Employment and Labor Market Statistics. The OECD makes available time series of stocks of unemployed and employed at rather aggregate levels. Like the EULFS, those data are produced based on countries’ labor force surveys data. Although for some countries the period covered is longer than the EULFS, the data do not include estimates of the ILO transition probabilities.

2.2 The point-identification problem

Let $Y^*_it$ denote a variable classifying individual $i$’s labor market state in period $t$ according to the ILO definitions. $Y^*_it$ can take three values: $E$ (employed), $U$ (unemployed), or $N$ (nonparticipant). The probability of moving from state $l \in Y^* = \{E, U, N\}$ in period $t - 1$ to state $k \in Y^*$ in period $t$ is denoted by

$$\pi_{lk} := P(Y^*_it = k|Y^*_{it-1} = l), \quad (1)$$

where $P(\cdot)$ denotes the probability function. To simplify the exposition, (1) presents probabilities unconditional on observed demographic variables (e.g. sex, age etc.). Those conditional
probabilities are of course of interest, and our analysis and results apply to them without any substantial changes.

With longitudinal data, the transition probabilities above can be consistently estimated using the sample analog of (1). However, as mentioned already, the EULFS does not include longitudinal identifiers, which makes that strategy infeasible. Instead, we model the EULFS sampling process for each country as a series of repeated cross sections. We classify each country into two groups depending on the availability of retrospective information on past labor market state. Consider first countries that do not collect retrospective information. To estimate (1) we use the following consecutive cross section random samples

\[ \{Y^\ast_{it}, W_i\}_{i \in S_t} \text{ and } \{Y^\ast_{jt-1}, W_j\}_{j \in S_{t-1}}, \]  

(TSCS)

where \( W \) is a vector of individual discrete characteristics such as sex, year of birth and region of residence.\(^5\) \( S_t \) and \( S_{t-1} \) are lists of individuals. Due to the panel dimension of the underlying national labor force surveys, a fraction of individuals are common across the two samples, but that information is not available in the EULFS data.\(^6\)

For countries with retrospective information, we use the following consecutive cross section random samples.\(^7\)

\[ \{Y^\ast_{it}, Y^{t-1}_{it}, W_i\}_{i \in S_t} \text{ and } \{Y^\ast_{jt-1}, Y^{t-1}_{jt-1}, W_j\}_{j \in S_{t-1}}, \]  

(TSCS-R)

where \( Y^{t-1}_{it} \) denotes the subjective labor market state of individual \( i \) at time \( t - 1 \) recalled at time \( t \), and \( Y^{t-1}_{jt-1} \) denotes the subjective labor state of individual \( j \) at time \( t - 1 \) reported in the same period. In Section 4.2 we describe those variables more precisely. At this stage, it is sufficient to note that, in general, \( Y^{t-1}_{it} \) cannot be used as a direct measurement of \( Y^\ast_{t-1} \), since its classification is conceptually distinct from the ILO.

To understand how point-identification of (1) may be obtained, we start by showing that,

\(^5\)All EULFS variables of interest are either discrete or are discretized by Eurostat due to privacy reasons (e.g. age).

\(^6\)The EULFS includes a variable (INTWAVE) that indicates the sequence number of the period in which the individual is in the sample. Therefore, one could construct non-overlapping samples, albeit of much smaller size.

\(^7\)To simplify the exposition, we describe (TSCS) and (TSCS-R) as composed of cross-sectional random samples. In reality, the cross-sectional samples are stratified. However, this involves no loss of generality. Since the EULFS includes sample weights, using them is equivalent to working with random samples.
without further assumptions, (TSCS) and (TSCS-R) only set-identify the ILO transition probabilities. Intuitively, while (TSCS) and (TSCS-R) provide information on the marginal distributions of $Y_t^\star$ and $Y_{t-1}^\star$, that information is insufficient to identify the joint distribution of $Y_t^\star$ and $Y_{t-1}^\star$, which is what (1) is. To see this formally, let $\mathcal{Y}^\star = \{E, U, N\}$ denote the support of $Y_t^\star$ and $|\mathcal{Y}^\star| = 3$ its cardinality. Define similarly the supports and cardinalities of $W_t$, $Y_{t-1}$ and $Y_{t-1}$. The Law of Total Probability (LTP) allows us to relate the ILO transition probabilities $\pi_{lk}$ to the conditional transition probabilities $\pi_{lk}(w) := P(Y_t^\star = k | Y_{t-1}^\star = l, W = w)$ by the expression below

$$\pi_{lk} = \sum_{w \in \mathcal{W}} \pi_{lk}(w) P(W = w).$$ (2)

Again, by the LTP, the conditional transition probabilities $\pi_{lk}(w)$ satisfy

$$P(Y_t^\star = k | W = w) = \sum_{l \in \mathcal{Y}^\star} \pi_{lk}(w) P(Y_{t-1}^\star = l | W = w) \quad \forall k, w \in \mathcal{Y}^\star \times \mathcal{W}. \tag{3}$$

(TSCS) point-identifies $P(W = w)$ in equation (2), and $P(Y_t^\star = k | W = w)$ and $P(Y_{t-1}^\star = l | W = w)$ in equation (3). Then, identifying $\pi_{lk}$ boils down to characterizing the solutions of (3) in the unknowns $\pi_{lk}(w)$. Equation (3) is a system of $|\mathcal{Y}^\star| \times |\mathcal{W}|$ linear equations with $|\mathcal{Y}^\star|^2 \times |\mathcal{W}|$ unknowns. Since the number of unknowns is greater than the number of equations, the solution, if it exists, is not unique.\footnote{Cross and Manski (2002) characterize the set of solutions to this system of equations, that is, the identified set of $\{\pi_{lk}(w)\}_{l,k \in \mathcal{Y}^\star}$.} A similar set-identifying result follows from (TSCS-R) because the recalled state $Y_{t-1}$ does not coincide with the unobserved lagged ILO state $Y_{t-1}^\star$. Then, the available strategies to restore point-identification from (TSCS) and (TSCS-R) involve reducing the number of unknowns in the system of linear equations (3) by excluding some of the conditioning variables in $P(Y_t^\star = k | Y_{t-1}^\star = l, W = w)$ (see e.g. Moffitt, 1993 and Cross and Manski, 2002).\footnote{Moffitt (1993) proposes to identify transition probabilities from repeated cross sections by assuming that they are time invariant. Our validation exercise shows that the ILO transition probabilities are not time invariant.} In Sections 3 and 4, we will state, and analyze the plausibility of, the assumptions point-identifying the ILO transition probabilities using (TSCS) and (TSCS-R), respectively.
2.3 The point-identification problem with duration data

An alternative approach to using longitudinally-linked observations of individual labor market states to measure transition probabilities relies on cross-sectional counts of individuals in labor market states at different durations. Two papers pursue this approach for European countries. Elsby et al. (2013) estimate the unemployment outflow and inflow probabilities using OECD time-series data on the stocks of individuals in short-term unemployment, unemployment and employment. While those probabilities provide very useful information, they do not estimate the elements of (1), but rather sums of some of those elements. Specifically, they estimate the unemployment outflow rate \( (\pi^U + \pi^N) \) and the unemployment inflow rate \( (\pi^E + \pi^N) \).

Borowczyk-Martins (2021) estimates employer-to-employer transition probabilities combining time-series data on the stocks of individuals in short-term nonemployment and employer spells and in nonemployment, which he estimates on EULFS microdata. As a by-product of his approach, he estimates the nonemployment outflow and inflow probabilities. Again, his approach does not recover the elements of (1), but rather sums of those elements, namely the nonemployment outflow probability \( (\pi^{NE} + \pi^U) \) and the nonemployment inflow probability \( (\pi^{EN} + \pi^E) \).

Combining the various measures of duration and other restrictions satisfied by the probabilities in (1) (e.g. probabilities lie within the unit interval and the sum of unemployment at \( t - 1 \) and worker flows in and out of unemployment from \( t - 1 \) to \( t \) add up exactly to unemployment at time \( t \)) is not sufficient to nonparametrically identify all the elements of (1).\(^{10}\)

3 Time series of cross sections

This section first presents the assumptions securing point-identification of ILO transitions from TSCS data, and discusses their implications for empirical applications. Next, it uses UK Labor Force Survey (UKLFS) panel data to assess the validity of those restrictions.

3.1 Point-identification result

To obtain point identification from TSCS one needs to reduce the number of unknowns in the system of linear equations (3) by excluding some of the conditioning variables in \( P(Y_t^* = \)

\(^{10}\)Using data from Canada Nakamura et al. (2020) estimate \( \pi^U \) and \( \pi^E \) under the assumption that \( \pi^{NE} \) takes the midpoint value of its boundary values in each period.
Since \( W \) may contain many variables, the restrictions can exclude one or several variables at the time. Since validity of excluding several variables hinges upon the validity of excluding one variable at the time, for identification analysis it suffices to consider only the latter type of restriction. Let us partition \( W = (X, Z) \), where \( Z \) is the variable that one would like to exclude from \( P(Y_t^* = k|Y_{t-1}^* = l, W = w) \), and \( X \) is a control variable.

Consider now the following assumption:

**Exclusion Restriction** \( Z \). The variable \( Z \) does not predict ILO state \( Y_t^* \) after controlling for lagged ILO state \( Y_{t-1}^* \) and the control variable \( X \), that is,

\[
P(Y_t^* = k|Y_{t-1}^* = l, X = x, Z = z) = P(Y_t^* = k|Y_{t-1}^* = l, X = x) \forall k, l, z, x.
\] (ER-\( Z \))

We then have the following point-identifying result:

**Proposition 1.** Assume that \( X \) and \( Z \) are discrete. For a given \( x \in X \), define the matrices

\[
A(x) := \{P(Y_t^* = l|X = x, Z = z)\}_{z \in Z, l \in Y^*} \quad \text{and} \quad B(x) := \{P(Y_{t-1}^* = l|X = x, Z = z)\}_{z \in Z, l \in Y^*}.
\]

Let (ER-\( Z \)) and the following **Rank Restriction** hold

\[
\text{rank}[B(x)] = |Y^*| \quad \text{for every } x \in X.
\] (RR-\( Z \))

Then,

\[
\pi_{lk}(x) = \left[ [B(x)^T B(x)]^{-1} B(x)^T A(x) \right]_{l,k}
\] (4)

and (TSCS) point-identifies the ILO transition probabilities \( \{\pi_{lk}\}_{l,k \in Y^*} \).

To supply some intuition on the identification problem and solution consider a two-state model of the labor market where individuals are either employed (E) or unemployed (U).\(^{11}\) First, to see the lack of identification from TSCS in this context, consider two consecutive cross sections such that the probabilities of individuals in employment and unemployment are constant over time (e.g. \( p_t^E = p_{t-1}^E = 0.9 \) and \( p_t^U = p_{t-1}^U = 0.1 \)). There are many possible

\(^{11}\)We thank an anonymous referee for suggesting this discussion.
values of $\pi^E$, $\pi^U$ consistent with those data. In particular, any pair $\pi^E$, $\pi^U$ such that $\pi^E = \pi^U$ is consistent with those data, implying that their values are not point-identified.

To see how identification is obtained, consider the probabilities of individuals in each state across two periods and two different labor market segments (1 and 2), denoted $p^L(\mathbf{x})$ where $l$ indexes the labor market state and $x$ the labor market segment. By the LTP, we have the following system of equations:

\begin{align}
 p^E_t(1) &= p^E_{t-1}(1)\pi^{EE}(1) + p^U_{t-1}(1)\pi^{UE}(1) \quad \text{(EX-1)} \\
 p^U_t(1) &= p^E_{t-1}(1)\pi^{EU}(1) + p^U_{t-1}(1)\pi^{UU}(1) \quad \text{(EX-2)} \\
 p^E_t(2) &= p^E_{t-1}(2)\pi^{EE}(2) + p^U_{t-1}(2)\pi^{UE}(2) \quad \text{(EX-3)} \\
 p^U_t(2) &= p^E_{t-1}(2)\pi^{EU}(2) + p^U_{t-1}(2)\pi^{UU}(2) \quad \text{(EX-4)}
\end{align}

This a system of four equations and eight unknowns. Therefore, without further restrictions, we cannot identify the transition probabilities of each labor market segment nor the aggregate transition probabilities. Our identification strategy assumes that the transition probabilities are common across different labor-market segments, i.e. $\pi^{lk}(1) = \pi^{lk}(2)$ for all $l, k \in U, E$. Under that assumption (the exclusion restriction) the system becomes exactly identified and point-identification is secured. Beyond the validity of the assumption that the transition probabilities are common across labor-market segments, for this strategy to work well in practice the equations in each pair (EX-1), (EX-3) and (EX-2), (EX-4) must be sufficiently different between them (the rank condition). In other words, the probabilities in each labor market state must be sufficiently different across labor-market segments. If that is not the case, identification fails in practice.

### 3.2 Estimation

The point-identification strategy laid out in the previous section offers a direct route to estimate $\pi^{lk}$. The matrices $A(x)$ and $B(x)$ are contingency tables between $Y_t^*/Y_{t-1}^*$ and $Z$ conditional on different values of the control variable $X$, which can be computed using respectively the cross-sectional samples (TSCS) and (TSCS-R). The sample analog estimator based on (ER-Z) is
$$\hat{\pi}^{lk}(x) := \left[ [\tilde{B}(x)^T \tilde{B}(x)]^{-1} \tilde{B}(x)^T \tilde{A}(x) \right]_{l,k}$$

with $\tilde{A}(x)$ and $\tilde{B}(x)$ denoting, respectively, the sample analog of $A(x)$ and $B(x)$. $\hat{\pi}^{lk}(x)$ is the ordinary least squares estimator obtained from regressing $\tilde{A}(x)$ on $\tilde{B}(x)$.

Using equation (2), one can then obtain the aggregate ILO transitions ($\hat{\pi}^{lk}$)

$$\hat{\pi}^{lk} = \sum_{x \in \mathcal{X}} \hat{\pi}^{lk}(x) \bar{p}(x),$$  \hspace{1cm} (SA)$$

where $\bar{p}(x) = n^{-1} \sum_{i \in S} 1(Y^*_i = l) 1(X = x)$ for $S := S_t \cup S_{t-1}$, that is, the fraction of individuals with $X = x$ across two consecutive cross-sectional samples, where $n$ denotes the count of all individuals in the combined sample.

This sample analog estimator has two drawbacks. First, it does not restrict the estimated ILO probabilities to be between zero and one, which can result in nonsensical estimates. Second, it does not restrict the estimated probabilities to match the sample proportions of individuals in each ILO state at time $t$ and $t - 1$, which can result in unnecessarily imprecise estimates.

To address these two drawbacks, we compute a constrained sample analog (CSA) estimator, which forces the estimated transition probabilities to satisfy those two restrictions.

Define the sample proportions of individuals in each ILO state and with $X = x$ at time $t$ and $t - 1$ as follows:

$$\bar{m}_{t,t}(x) := n_t(x)^{-1} \sum_{i \in S_t} 1(Y^*_i = l) 1(X = x)$$ and

$$\bar{m}_{t-1,t}(x) := n_{t-1}(x)^{-1} \sum_{i \in S_{t-1}} 1(Y^*_{i-1} = l) 1(X = x),$$

where $n_t(x) := \sum_{i \in S_t} 1(X_i = x)$ and $n_{t-1}(x) := \sum_{i \in S_{t-1}} 1(X = x)$ are the sample proportions of individuals in period $t$ and $t - 1$ with $X = x$. 
The constrained sample analog estimator of the conditional transition probabilities is

$$\arg \min_{\{\hat{\pi}_{lk}(x)\}_{l,k \in \mathcal{Y}}} \sum_{z \in \mathcal{Z}} \left| \bar{a}_{zk}(x) - \sum_{l \in \mathcal{Y}^*} \hat{\pi}_{lk}(x) \bar{b}_{zl}(x) \right|^2$$

subject to

$$0 \leq \hat{\pi}_{lk}(x) \leq 1 \text{ for all } l, k$$  \hspace{1cm} (CSA-R1)

$$\sum_{l \in \mathcal{Y}^*} \hat{\pi}_{lk}(x) \bar{m}_{t-1,l}(x) = \bar{m}_{t,k}(x) \text{ for all } k \in \mathcal{Y}^*,$$  \hspace{1cm} (CSA-R2)

$$\sum_{k \in \mathcal{Y}^*} \hat{\pi}_{lk}(x) = 1 \text{ for all } l \in \mathcal{Y}^*.$$  \hspace{1cm} (CSA-R3)

where $\bar{a}_{zk}(x)$ and $\bar{b}_{zl}(x)$ are, respectively, elements of $\bar{A}(x)$ and $\bar{B}(x)$.

Restriction (CSA-R1) forces the estimated transition probabilities to be between 0 and 1, while restrictions (CSA-R2) and (CSA-R3) force them to be consistent with the sample proportions in each labor market state at both time $t$ and $t-1$.

Under (RR-Z), the constrained optimization problem above has an a.s. strictly convex objective function and an a.s. convex feasible set. Hence, if the feasible set is nonempty, its solution exists and is unique a.s..

As with sample analog estimator, the constrained sample analog estimator for the aggregate transition probabilities is obtained by aggregation of the conditional transition probabilities

$$\hat{\pi}_{lk} = \sum_{x \in \mathcal{X}} \hat{\pi}_{lk}(x) \hat{p}(x).$$  \hspace{1cm} (CSA)

### 3.3 Empirical implementation

The point-identification strategy in Proposition 1 imposes three important requirements on candidate excluded variables $Z$. First, realizations of the excluded variable must be observed for all individuals in any two consecutive cross-sectional samples. This implies that the distribution of $Z$ must be plausibly time constant relative to the period of observation. By definition, all time-invariant individual characteristics, e.g. sex and birth-cohort, satisfy this condition. Moreover, variables that are effectively time invariant across two consecutive cross sections can also be considered. For example, even if some individuals change region of residence across quarters, they represent a very small fraction of the population, so that the distribution of
region of residence can be taken as fixed across two consecutive cross sections. On the contrary, variables recording individuals’ labor market states are likely to fail this condition. It is well known that the distributions of labor market states along several dimensions (e.g. not only ILO states, but also hours worked, search activity etc.) have very salient dynamics. Perhaps more importantly, many variables in the EULFS are not collected for all individuals in a given cross-section. This is because the structure of labor force survey interviews is determined by the individual’s recorded labor-market state in the reference week. Therefore, most questions that are asked to employed workers are not asked to nonemployed workers, and vice-versa.

Second, the exclusion restriction requires that the ILO transition probabilities are not different across different values of the excluded variable. In practice, this restriction is problematic because it rules out permanent differences in the levels of ILO transitions across different values of the excluded variable. In other words, any unobserved high-frequency labor demand or supply shock that does not produce homogeneous effects across different values of the excluded variable will lead to a failure of the exclusion restriction. In general, neither economic theory nor empirical knowledge of labor markets offer clear directions to variables satisfying this condition. Irrespective of the chosen variable, one possible avenue to slacken the exclusion restriction is to include a large list of variables among the control variables $X$, but there is no obvious reason to expect this avenue to work.

The third and last point-identifying condition is the rank restriction. It implies two conditions. The first is that the support of the excluded variable is at least as large as the number of ILO states. In practice, this excludes a few variables (e.g. sex), but otherwise is easy to satisfy. The second is that, for all possible values of the control variable, the proportions of individuals in each lagged ILO state (i.e. the rows of the $B(x)$ matrices) are not proportional across different values of the excluded variable. In other words, for each $B(x)$ matrix, it should not be possible to write any row as a linear combination of the other rows. Consider the case without any control variables (so that there is only one matrix $B$) and where region of residence is the chosen excluded variable. If the proportions of individuals across ILO states are the same across regions, then the rank condition fails. While there are specific statistical procedures to test this rank assumption, in practice it is easy to detect a failure of this assumption in the simplest cases.
3.4 Validation using UK Labor Force Survey Data

In our validation exercise we use the UKLFS, which is used to produce the EULFS for the UK. We start by comparing transition probabilities estimates based on EULFS TSCS data to UKLFS longitudinal estimates. Then, we test the exclusion restriction directly with panel UKLFS data, where we include a large set of covariates.

3.4.1 The UKLFS data

The UKLFS surveys households living in private addresses and is representative of the UK population. Since 1992 the UKLFS is structured as a five-wave rotating panel with a quarterly frequency. The current sample covers around 37,000 responding households per quarter. We use the two-quarter longitudinal extracts provided by the UK Data Service. The sample covers males between the ages of 18 and 64 and women between the ages of 18 and 59.

3.4.2 Comparing TSCS and longitudinal estimates

We start by comparing transition probabilities estimates based on EULFS TSCS data to UKLFS longitudinal estimates. We conduct our analysis using all quarters from 2009 to 2014. Our chosen excluded variable is region of usual residence (we divide the UK into 12 regions). We experimented with other candidate variables and region appeared to perform best.

Figure 1 reports three alternative times series of estimates of all six off-diagonal transition probabilities in (1). The solid green line denotes the time series of estimates obtained by linking longitudinally individual observations across quarters using the ILO classification of labor market states. We refer to it as the longitudinal estimate and denote it by the acronym LGN. We compare it to two alternative TSCS estimates based on our IV and excluding any control variable. The SA estimates are denoted by the red dotted line, whereas the blue dashed line denotes the CSA estimates. To compute the three estimates we did not use cross-sectional sample weights, since we think it facilitates the interpretation of the observed differences across estimates.

We highlight two main features in Figure 1. First, in general, both the dashed and dotted lines are very far from the solid line, indicating a failure of the assumptions underpinning the

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12We obtained UKLFS microdata from the UK Data Service. Access to the data is restricted to accredited researchers. For more information, check https://www.ukdataservice.ac.uk/.
Figure 1: Comparing UK ILO Transition Probabilities Estimates

Notes: UKLFS quarterly data, 2009:2 – 2014:4. Time series of estimates based on the Longitudinal (LGN), Sample Analog (SA) and Constrained Sample Analog (CSA) estimators are reported in percent. For CSA and SA, the excluded variable is region of residence and no controls are included. The range of the vertical axis is bounded by the maximum and minimum value of the LGN estimate in the following way (numbers are expressed in percentage points): (a), (b) \[
\min\{\pi_{\text{LGN}}\} - 5, \max\{\pi_{\text{LGN}}\} + 5 \]; (c), (d) \[
\min\{\pi_{\text{LGN}}\} - 15, \max\{\pi_{\text{LGN}}\} + 15 \]; and (e), (f) \[
\min\{\pi_{\text{LGN}}\} - 35, \max\{\pi_{\text{LGN}}\} + 35 \]. The black solid horizontal line denotes zero.
TSCS point-identification strategy in Proposition 1. Having said this, we also observe that for specific quarters all three estimates are quite close to each other, indicating that it is not the case that the point-identifying restrictions are never satisfied. Without validation data, one does not know when the point-identification assumptions are more likely to be satisfied, so in practice knowing that sometimes the restriction is satisfied is not necessarily useful.\textsuperscript{13}

The second point we want to emphasize is the overall better performance of the CSA estimator vis-a-vis the SA estimator. In all six plots the dotted line is located further apart from the solid line compared to the dashed line. Moreover, the dotted line often produces estimates below and above 100\% (we do not show the latter to preserve visual clarity).

### 3.4.3 Assessing the exclusion restriction

To test the exclusion restriction (ER-Z) directly and quantify the extent of its failure, we estimate a multinomial logit model for the individual transition probabilities, which includes as regressors sets of indicator variables for the lagged ILO state, region of residence (the candidate excluded variable), and the following control variables (sex, birth cohort, and education). In this setting, a test of the validity of the exclusion restriction boils down to the null hypothesis that the coefficients associated to region of residence are all jointly equal to zero. There are many candidate variables to exclude, but we narrow our validation exercise to the variable recording region of residence, which is our preferred candidate.\textsuperscript{14}

Figure 2 reports the p-value from the Likelihood Ratio test associated to the null hypothesis that the coefficients for the region of residence are jointly zero. Consistent with Figure 1, inspection of Figure 2 shows that, in most quarters, the null hypothesis is rejected at very high levels of statistical confidence.

A failure of the rank condition could be detected from (TSCS) without resorting to a validation dataset, so we do not attempt to test this assumption.

\textsuperscript{13}Note that the data has a quarterly frequency, so this effect is not the result of the plot line connecting data points that are far apart.

\textsuperscript{14}Results for other candidate exclude variables, like birth cohort, are available upon request.
For countries with TSCS data including retrospective information, there are additional strategies to point-identify the ILO transitions. This section follows a similar structure to Section 3. First, we state all point-identification strategies for (TSCS-R), and offer a measurement-error interpretation of those restrictions. Next, we compare TSCS and longitudinal estimates using Portuguese Labor Force Survey (PLFS) data, and document the patterns of measurement error in the recalled state. Last, we test the exclusion restrictions directly with PLFS panel data.

4.1 Point-identification results and estimation

All the relevant variables available in countries with TSCS are also available for the countries in the EULFS with retrospective information. Therefore, the exclusion restriction presented in Section 3.1 can be used for countries with retrospective information as well. But (TSCS-R) allow for two additional exclusion restrictions to obtain point-identification. The first alternative strategy is to exclude the lagged ILO variable.

**Exclusion Restriction** $Y_{t-1}^*$. *Lagged ILO state $Y_{t-1}^*$ does not predict current ILO state $Y_t^*$*
after controlling for recalled state \( Y_{t-1}^{\ast} \) and \( X \):

\[
P(Y_t^\ast = k | Y_{t-1}^\ast = l, Y_t^{t-1} = l, X = x) = P(Y_t^\ast = k | Y_{t-1}^\ast = l, X = x) \quad \forall k, l, x. \quad (ER-Y_{t-1}^\ast)
\]

This leads to the following result:

**Proposition 2.** Let the Exclusion Restriction \((ER-Y_{t-1}^\ast)\) and the Support Restriction \((SR-Y_{t-1}^\ast)\) hold

\[
Y^\ast = Y^{t-1} \quad (SR-Y_{t-1}^\ast)
\]

Then, a single cross section with retrospective data in \((TSCS-R)\) point-identifies the ILO transitions \( \{ \pi_{lk} \}_{l,k} \).

The support restriction \((SR-Y_{t-1}^\ast)\) requires that the recalled state variable has at least as many labor market states as the ILO state variable. As shown in Figure 7 of the Appendix, this restriction is satisfied in the EULFS. Proposition 2 suggests the sample analog estimator \( P(Y_t^\ast = k | Y_{t-1}^{t-1} = l) \), which requires a single cross section with retrospective information. This sample analog estimator produces estimates that are in the unit interval but, in general, are not consistent with the sample proportions of individuals in each ILO state at \( t - 1.15 \)

We state Proposition 2 to offer a complete list of point-identification strategies for \((TSCS-R)\). We do not argue that the recalled state is actually measuring the lagged ILO state (though there are reasons to believe that they are closely related). Analyzing the exclusion restriction \((ER-Y_{t-1}^\ast)\) is useful to show that one can justify using the sample analog of \( P(Y_t^\ast = k | Y_{t-1}^{t-1} = l) \) with weaker conditions than stating that \( Y_t^{t-1} = Y_t^{t-1} \). The latter assumption cannot be tested from \((TSCS-R)\), but it is falsifiable from a validation dataset. In Section 4.2 we will delve into these differences using PLFS data.

The second point-identifying strategy with retrospective information is to exclude the recalled state as in the following assumption.

**Exclusion Restriction** \( Y^{t-1} \). The recalled state \( Y^{t-1} \) does not predict current ILO state \( Y_t^\ast \)

\[15\text{We could enforce the flow equation } P(Y_t^\ast = k) = P(Y_t^\ast = k | Y_{t-1}^{t-1} = l) + \eta_{lk} P(Y_{t-1}^\ast = l), \text{ where } \eta_{lk} = 1 - P(Y_t^\ast = k | Y_{t-1}^{t-1} = l) - P(Y_t^\ast \neq l | Y_{t-1}^\ast = k), \text{ but do not do it in our validation exercise.} \]
after controlling for lagged ILO state $Y_{t-1}^*$ and $X$:

$$P(Y_t^* = k|Y_{t-1}^* = l, Y_{t-1} = s, X = x) = P(Y_t^* = k|Y_{t-1}^* = l, X = x) \quad \forall l, k, s, x. \quad \text{(ER-}$Y_{t-1}$)$

Furthermore, if one assumes that the distributions of $Y_{t-1}^*$ and $Y_{t-1}$ are the same, point-identification of the ILO transition probabilities follows from (ER-$Y_{t-1}$) by setting $Z_i = Y_{it-1}^*$ and $Z_j = Y_{jt-1}$ as the excluded variable in Proposition 1. In this case, (ER-$Y_{t-1}$) amounts to assuming that recalled state does not predict current ILO state after controlling for lagged ILO state and any potential control covariates. In the next subsection, we will interpret the implications of these assumptions in terms of patterns of measurement error that are consistent with it.

### 4.2 A measurement-error interpretation

To interpret the implications of point-identification strategies based on the subjective labor market state variables, it is useful to describe the relations between the ILO states and subjective states variables in terms of measurement errors.

With retrospective information, each cross section includes two additional variables: recalled state and subjective state. The former pertains to the individual’s labor market state one year ago and the latter to the labor market state in the reference week. Unlike the ILO classification, in both cases the concept of unemployment is not necessarily predicated on the individual’s recent job search activity and availability to start working in the very short run. The subjective classification of labor market state is left to the respondent’s own perception. See Figure 7 in the Appendix for more details.

Figure 3 illustrates the relations among the labor market state variables, where the variables denoted in red are not available in the EULFS, and those denoted in blue are available in both the EULFS and the PLFS. The top horizontal arrow denotes the relation we want to estimate (the ILO transitions). The first type of measurement error (classification error) is denoted by the vertical arrow and is defined as the difference between $Y_{it-1}^*$ and $Y_{it-1}$. Both $Y_{it-1}^*$ and $Y_{it-1}$ record the individual’s labor market state in the survey’s reference week at $t - 1$ and are collected at the same moment (the interview). However, they are based on different labor market definitions and responses to different survey questions. As such, differences between
them are informative about classification error. The second type of measurement error (recall error) is denoted by the lower horizontal arrow, and is defined as the difference between \( Y_{it-1} \) and \( Y^t_{it-1} \). Both \( Y_{it-1} \) and \( Y^t_{it-1} \) record individuals’ subjective labor market state in same calendar week. However, they are reported at different time periods (the former at \( t-1 \) and the latter at \( t \)). Hence, the mapping between them is informative about recall error. Last, the difference between \( Y^t_{it-1} \) and \( Y^t_{it-1} \), which we call proxy error, captures both the recall and classification errors, as well as any additional measurement error.

To interpret the assumptions delivering point-identification from (TSCS-R), we start by defining proxy error. Write the recalled state as a mixture of the lagged ILO state and a latent variable \( L_{it-1} \) as in

\[
Y^t_{it-1} = C_{it-1}Y^*_{it-1} + (1 - C_{it-1})L_{it-1},
\]

where \( C_{it-1} \) is an unobserved binary variable taking value one when the recalled and ILO lagged states are equivalent and zero otherwise. The proxy error is

\[
E_{it} := Y^t_{it-1} - Y^*_{it-1} = (C_{it-1} - 1)Y^*_{it-1} + (1 - C_{it-1})L_{it-1}.
\]

If the indicator \( C_{it-1} \) for the absence of proxy error does not predict the ILO state given the lagged ILO state as in

\[
P(Y^*_{it} = k|Y^*_{it-1} = l, C_{t-1} = 1) = P(Y^*_{it} = k|Y^*_{it-1} = l),
\]

then \( \text{(ER-}Y^*_{it-1}) \) holds.
If the indicator $C_{it-1}$ and the latent variable $L_{it-1}$ do not predict the ILO state given the lagged ILO state as in

$$P(Y^*_t = k | Y^*_{it-1} = l, C_{t-1} = c, L_{it-1} = s) = P(Y^*_t = k | Y^*_{it-1} = l),$$

for all $c, s$ then (ER-$Y^{t-1}$) holds.

An example of proxy error violating both restrictions above is the case where individuals make classification and recall errors depending on their current ILO state given that they were ILO unemployed in previous period. It is immediate that, if there is no proxy error, that is $Y^*_{it} = Y^*_{it-1}$, (ER-$Y^{t-1}$) and (ER-$Y^{t-1}$) both hold.

### 4.3 Validation using Portuguese Labor Force Survey data

In this section we estimate the ILO transition matrix with EULFS TSCS yearly data using a simple specification without controls and two alternative IV (recalled state and lagged ILO state), and show that they differ substantially from the longitudinal estimates based on PLFS data. Next, we use PLFS panel data to show why the two point-identification strategies fail by

(i) documenting evidence of recall, classification and proxy errors in the recalled state variable, and

(ii) by rejecting the exclusion restriction for the recalled state variable even when controlling for a large number of covariates.

#### 4.3.1 The PLFS data

The PLFS collects information on individuals aged 15 or older who live in private households.\footnote{We obtained PLFS microdata from Statistics Portugal. Access to the data is restricted to researchers associated to national research centers. For more information, check \url{https://www.ine.pt/xportal/xmain?xpid=INE&xpgid=ine_main}.} The full implementation of the survey design prescribed by Eurostat came into effect in the first quarter of 2011. We conduct our analysis using all years from 2011 to 2018. Because we are primarily interested in assessing the performance of our estimation method, we select individuals who have information on the three labor market state variables (ILO state, recalled state and lagged ILO state). This means that we have, at most, two observations per individual one year apart from each other, on their last (sixth) and next-to-last (fifth) quarter in the sample. In addition, our sample is restricted to individuals of the working age (between 18 to 64 years...}
In our application we will work with a three-valued version of the variables based on individuals’ subjective classification. We emphasize that in the PLFS the subjective variables are asked to all individuals irrespective of their ILO state and that the reference period is explicitly included in the survey question (i.e. individuals are supposed to make statements about a specific week, either the reference week or the week exactly one year before the reference week). Last, although the frequency of the PLFS is quarterly, our estimation data set has a yearly frequency. We want to avoid having very small number of observations in the cells of the contingency table formed by the ILO state categories and the subjective state categories.\(^{17}\)

### 4.3.2 Comparing TSCS and longitudinal estimates

Figure 4 reports four alternative times series of all six off-diagonal transition probabilities in (1). The solid line denotes the estimates obtained by linking longitudinally individual observations using the ILO states (denoted LGN). The short-dashed line shows the sample-analog estimates based on \(\text{ER-}Y_{t-1}^*\) (denoted SSA, for single cross-section sample analog). The dotted line shows the the sample-analog estimates based on \(\text{ER-}Y_{t-1}^t\), where the subjective states are used as the excluded variable, and where the dashed line displays the estimates based on the same point-identification strategy but using the constrained sample analog estimator.

We highlight two main features in Figure 4. First, perhaps surprisingly the performance of the estimators using the retrospective information state is quite poor. Although they track the dynamics of the longitudinal estimates quite well, their levels are systematically different. Second, while none of the TSCS estimators performs well, surprisingly it appears that the less plausible point-identification strategy (the one based on \(\text{ER-}Y_{t-1}^*\)) performs somewhat better.

### 4.3.3 Measurement error in recalled state

The systematic differences between the longitudinal and the TSCS estimates in Figure 4 suggest the presence of measurement error in the recalled state variable. In this section we quantify the extent of all forms of measurement error described in Figure 3. Figure 5 shows time series

\(^{17}\)Specifically, the number of individuals who are ILO unemployed and subjectively classify themselves as employed is very small and even zero in some quarters. The main reason for the presence of such small numbers at a quarterly frequency in our sample is the restriction to individuals having at least two observations one year apart. This implies that we keep at most two observations per individual, when in reality most individuals stay in the sample for six quarters.
(a) Transition probability from E to U: $\pi_{EU}$

(b) Transition probability from E to N: $\pi_{EN}$

(c) Transition probability from U to E: $\pi_{UE}$

(d) Transition probability from U to N: $\pi_{UN}$

(e) Transition probability from N to E: $\pi_{NE}$

(f) Transition probability from N to U: $\pi_{NU}$

Figure 4: Comparing Portugal’s ILO Transition Probabilities Estimates

Notes: PLFS yearly data, 2013 – 2018. Time series of estimates based on the Longitudinal (LGN), Single cross-section Sample Analog (SSA), Sample Analog (SA) and Constrained Sample Analog (CSA) estimators are reported in percent. For CSA and SA, the IV is recalled state and no controls are included. The range of the vertical axis is bounded by the maximum and minimum value of the LGN estimate in the following way (numbers are expressed in percentage points): (a), (b), (c) $\{\text{Min}\{\pi_{\text{LGN}}\} - 2.5, \text{Max}\{\pi_{\text{LGN}}\} + 2.5\}$; (d) $\{\text{Min}\{\pi_{\text{LGN}}\} - 2, \text{Max}\{\pi_{\text{LGN}}\} + 2\}$; and (e), (f) $\{\text{Min}\{\pi_{\text{LGN}}\} - 15, \text{Max}\{\pi_{\text{LGN}}\} + 5\}$. The black solid horizontal line denotes zero.
of the sample average of three sets of probabilities estimates. Plot (a) displays time series of
the average probability that an individual classified in state \( j \) according to \( Y_{it-1}^\star \) is classified
in the same state according to \( Y_{it-1} \), one for each possible state. All three lines are below
100% and their levels differ markedly: the solid line (employment) is closer to 100% (fully
correct classification), the dashed line (unemployment) hovers around 90% and the dotted line
(nonparticipation) around 85%. Plot (b) displays time series of the average probability that
an individual classified in state \( j \) according to \( Y_{it-1} \) is classified in the same state according to
\( Y_{it-1}^l \). The lines indicate that recall error is similar to classification error for employment and
nonparticipation, but much higher for unemployment. Last, Plot (c) shows the proxy error.
That is, the time series of the average probability that an individual classified in state \( j \) according to \( Y_{it-1}^\star \) is classified in the same state according to \( Y_{it-1} \). Once again, the extent of proxy
error is higher for unemployment and nonparticipation, and lower for employment. In sum,
inspection of Figure 4 allows us to observe the following patterns of measurement error. First,
evidence of recall, classification and proxy errors is pervasive. Second, classification and proxy
errors have higher incidence among individuals who are ILO unemployed and nonparticipants.
Similarly, recall error has higher incidence among individuals who are subjectively unemployed
or nonparticipants. Third, recall and classification errors do not cancel out, and it is not clear
how they map onto proxy error.

4.3.4 Assessing the exclusion restriction

Similar to the validation exercise conducted for the UK EULFS data, we test the validity of
(ER-\( Y_{t-1} \)) using the subjective variables available in the PLFS using the same specification of
the individual transition probabilities.

Table 1 reports a subset of the coefficient estimates for every year when recalled state is
used as an IV. The set of controls includes sets of dummy variables for sex, birth cohort, years
of education, marital status and region of residence. As expected the coefficient estimates
associated with the ILO state (the upsilons) are all strongly statistically significant. What
is more surprising is that the coefficients associated with the recalled state (the zetas) are
considerably large and even more strongly statistically significant. The evidence for the rejection
of the exclusion restriction is overwhelming. Our hypothesis to rationalize the failure of the
Figure 5: Evidence of Different Forms of Measurement Error

Notes: PLFS yearly data, 2012-2018. All probabilities reported in percent. Plot (a) denotes the sample average of \( P(Y_{it-1} = j|Y_{it-1}^* = j) \) for \( j = E, U, N \). Plot (b) denotes the sample average of \( P(Y_{it-1}^* = j|Y_{it-1} = j) \) for \( j = E, U, N \). Plot (c) denotes the sample average of \( P(Y_{it}^* = j|Y_{it-1} = j) \) for \( j = E, U, N \).
Table 1: Test of the Exclusion Restriction in Portuguese Data

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LR test:

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Notes: PLFS, 2013 – 2018. The numbers reported in parentheses are p-values. The models include sets of dummy variables for quarter, sex, marital status, region of residence, education and birth cohort.

exclusion restriction is recall error. If individuals’ recollection has as its reference-point the current ILO state, then there is a link between the current ILO state and the recalled subjective labor market state even after controlling for the effect of the past ILO state, thereby violating the exclusion restriction.

5 Conclusion

This paper explores point-identification strategies for EULFS TSCS data (both with and without retrospective information on individual’s past labor state), and shows that they are not plausible by using validation panel data from Portugal and the UK. We draw two main im-
Applications from our results. First, we hope that our findings can help the case for including individual longitudinal information in the EULFS microdata available to researchers. This strategy has been followed by the US counterpart to the EULFS (the CPS), and the knowledge created both on the data and US labor markets has been extraordinary. Second, our point-identification approach relies on minimal assumptions, and our results show that, without further assumptions, EULFS TSCS data do not allow one to identify the ILO transition probabilities. An interesting avenue for future research is to explore the identification power of structural models of individual reporting behavior as in, for example, Shachar and Eckstein (2007).

A Appendix

A.1 Proofs

Proof of Proposition 1. For a given $x \in X$, define the matrix

$$\Gamma(x) := \{P(Y^*_t = l|Y^*_{t-1} = k, X = x)\}_{l,k}.$$ 

The two cross sections in (TSCS) point-identify, respectively, $A(x)$ and $B(x)$. By the Law of Total Probability,

$$P(Y^*_t = k|X = x, Z = z) = \sum_{l \in Y^*} \pi^{lk}(x) P(Y^*_{t-1} = l|X = x, Z = z).$$ 

Under Exclusion Restriction (ER-Z), one can re-write (3) as $A(x) = B(x)\Gamma(x)$. Under Rank Restriction (RR-Z), one has that $B(x)^T B(x)$ is invertible. Then, $\Gamma(x) = [B(x)^T B(x)]^{-1} B(x)^T A(x)$. Again, by the Law of Total Probability $\Pi = \mathbb{E}[\Gamma(X)]$. Hence, (TSCS) point-identifies $\Pi$ because $X$ is observed. \[\square\]

Proof of Proposition 2. (ER-$Y^*_{t-1}$) and (SR-$Y^*_{t-1}$) imply

$$\pi^{lk} = \sum_{w \in W} P(Y^*_t = k|Y^*_{t-1} = l, W = w) P(W = w).$$
Working-age population

Q1: Did you work (or were you absent from your job) last week?
- Yes
  - Employed
- No

Q2: Did you look for work in the past four weeks?

Q3: Are you available to start work in the next two weeks?
- Yes, Yes
  - Unemployed
- Otherwise
  - Nonparticipant

Figure 6: Measurement of International Labor Organization Labor Market State Classifications

The result follows from noticing that (TSCS-R) point-identifies $P(Y_t^* = k|Y_{t-1}^t = l, X = x)$. □

A.2 ILO and subjective labor market state classifications

Figure 6 illustrates the types of questions used to measure the three ILO states in labor force surveys. The EULFS ILO classification also includes ‘Military Service’ as an additional state. The incidence of this category is, however, negligible, so we ignore it in this paper.

To record individual subjective labor market states, EULFS respondents are asked the following questions: *What is (was) your main status in the labor market last week (one year ago)?* and have to select one among the following options displayed in Figure 7. As can be seen from Figure 7, there are more than three states. We include the last six items in a nonparticipation state.
What is (was) your main status in the labor market last week (one year ago)?

E - Carries out a job or profession, including unpaid work for a family business or holding, including an apprenticeship or paid traineeship, etc.

U - Unemployed.

N - Pupil, student, further training, unpaid work experience.

N - In retirement or early retirement or has given up business.

N - Permanently disabled.

N - In compulsory military service.

N - Fulfilling domestic tasks.

N - Other inactive person.

Figure 7: Survey questions and answers regarding respondents’ subjective labor market state

References


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