Employer-to-employer Transitions in Europe

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Abstract

I measure time series of the probabilities that an individual changes employer, separates from employment, and joins employment during the month, using cross-sectional data from the European Union Labor Force Survey covering 13 countries during the past two decades. Employer-to-employer mobility is large and accounts for a sizable fraction of worker mobility in all countries; its levels, both absolute and relative to nonemployment reallocation, vary considerably across countries. In most countries, the employer-to-employer probability exhibits large and procyclical variation. By contrast, there are no systematic cross-country patterns in the low-frequency evolution of employer-to-employer mobility.

Keywords: Employer-to-employer mobility; Labor market flows; Business cycles.
JEL codes: E24; J63.

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1 Introduction

The notion that individuals move directly across employers is a central feature of aggregate models of the labor market. Research on the macroeconomics of labor markets has shown that employer-to-employer transitions are important to answer key questions on aggregate labor market behavior, such as cross-sectional wage dispersion (e.g. Hornstein et al. (2011)), the dynamics of the employment distribution across firms (e.g. Moscarini and Postel-Vinay (2013)), unemployment dynamics (e.g. Robin (2011)), among others. However, the available evidence on transitions across employers without an intervening nonemployment spell (the employer-to-employer, or employer-change, probability) remains limited. In this paper I measure monthly time series of the aggregate probability that a worker changes employer during the month (the EE probability) for several European countries over a period of 15-20 years, including the Great and the Pandemic recessions and their preceding expansions. As a by-product of my approach, I also measure the aggregate employment-finding and employment-separation probabilities (the NE and EN probabilities, respectively). I use my estimates to document the patterns of cross-country variation in the levels and time variation in the three transition probabilities, with a focus on differences between Europe and the United States (US).

I start by comparing the average levels of the three probabilities across the 13 European countries in my sample and the US. First, I find substantial cross-country variation in the levels of the EE transition probability. From 2006 to 2019, average employer-to-employer transitions range from 0.43 percent (Italy) to 3.54 percent (Sweden), with a large fraction of countries displaying transition probabilities around 1 percent. In the US over the same period, the average EE probability is around 2 percent. For the vast majority of countries, flows across employers account for between 40 to 75% of total hires or separations. Second, the extent of cross-country variation in the EE probability is lower compared to that in the employment-finding and employment-separation probabilities, especially among prime-age individuals. More striking still are cross-country differences in the size of EE mobility relative to the size of transitions between employment and nonemployment. For example, like the US, the Nordic countries (Denmark, Finland and Sweden) display average EE probabilities around or above 2 percent, but their average levels of the employment-finding and employment-separation probabilities are much lower than in the US.

I then turn to the time-variation patterns in employer-to-employer mobility. Focusing first on cyclical variation, I find that there is a strong and negative comovement between changes in the unemployment rate and changes in the EE probability in the majority of countries. The few exceptions are the Czech Republic and Hungary, where that comovement is absent, and to a lesser extent Poland and Portugal, where that comovement is negative but very weak. Reassuringly, in most countries I find the usual direction of change in the employment-finding and employment-separation probabilities during cyclical episodes. The latter is characterized by large and short-lived spikes at the beginning of recessions, although it can remain persistently elevated in some countries (e.g. Italy, Portugal and Spain), whereas the former drops at the onset of recessions and recovers slowly as the unemployment rate declines. Focusing still on cyclical variation, I next document the relative cyclicality of transitions across employers vs transitions out of unemployment. In the US the recessionary fall in the EE probability is lower compared to the unemployment outflow probability, and this observation is important to inform and quantitatively assess recent models with search on the job (e.g. Moscarini and Postel-Vinay (2019), Eeckhout and Lindenlaub (2019) and Faberman et al. (forthcoming)). In the European countries in my sample, I find examples of similar, but also distinct, patterns. First, in all countries where the EE probability is not, or not always, procyclical (Poland, the Czech Republic, Portugal, and Hungary), I observe large recessionary falls in the unemployment-outflow probability. Second, Austria, Belgium, Finland and Sweden display joint dynamics of the two transition probabilities in the Great Recession that are quite similar to those of the US. In the remaining countries, the EE probability is clearly procyclical, and the size of its percentage drop is similar or larger (Germany) to that observed in the unemployment-outflow probability.

The final set of findings concern low-frequency variation in EE mobility. It is well-know that in the US EE mobility trended downwards in the first decade of the new century. Among the European countries in my sample I find that, from the eve of the Great Recession until the eve of the Covid-19 crisis, almost all types of possible developments are observed. Like in the US during that period, in Austria, Belgium, the Czech Republic, Finland and Germany, the extent of EE mobility remained largely unchanged. On the other hand, Portugal experienced very large increases in the EE probability, whereas Denmark, Italy, Poland, Spain, and the UK suffered significant falls in the employer-change probability.

To generate my results, I use microdata from the European Union Labor Force Survey (EULFS), which is Eurostat's harmonized version of European countries national labor force surveys used to measure official labor market indicators like the unemployment rate. The EU-LFS is the European counterpart to the US Current Population Survey (CPS), and in many respects it offers the longest and most comprehensive source of harmonized labor market data for several European countries. Researchers interested in measuring labor market transitions using the EULFS face a major challenge: the lack of individual longitudinal identifiers. Even though the national labor force surveys used to generate the EULFS have a longitudinal dimension, due to legal constraints, Eurostat makes the EULFS microdata available to researchers as a time series of cross sections. The majority of EE transition estimates in the literature are longitudinal, i.e. obtained by linking individual observations across two consecutive periods. I overcome that challenge by measuring EE transitions based on individuals' reported nonemployment and employer spell durations. Specifically, I extend Shimer (2012)'s continuous-time framework to measure transition rates between employment and nonemployment, and across different employers, using stocks of nonemployed and employed with their current employer in spells of any and short duration. First, I measure the nonemployment-to-employment and the employment-to-nonemployment rates by linking their dynamics to that of stocks of nonemployed at all and short durations. Second, I show how one can measure the transition rate across employers by using a continuous-time framework to describe the dynamics of the stocks of workers in employment and in short duration spells with their current employer. The dynamics of the stocks of workers in short-duration employer spells is driven by the dynamics of the rates at which workers move between employment and nonemployment, and the rate at which workers change employers. After estimating the former in the first step, I can obtain the employer-change rate by subtracting it from the employer-separation rate, which is equal to the negative of the logarithm of the fraction of employed workers last period who are in long-duration employer spells in the current period.

I implement my measurement approach to obtain monthly transition probabilities. Monthly transitions are directly comparable to US transition estimates measured with CPS data and, compared to quarterly or yearly transitions, are less exposed to time-aggregation bias. My implementation leverages on two features of the redesigned structure of the EULFS, adopted from the late 1990s until the mid 2000s in all member countries. First, in order to measure the duration of nonemployment and employer spells I combine information on the reference month and the spell start dates (month and year), which are asked to all survey respondents with a previous employment experience and in employment, respectively. Second, I explore the fact that EULFS interviews are evenly distributed across all weeks of the calendar year to measure stocks of nonemployed and employed with their current employer at all and short duration for every calendar month. That second feature further allows me to implement a consistent definition of spells of short duration for monthly transitions, which is *five weeks or less*, i.e. neither *less than or equal to zero months*, nor *less than or equal to one month*. Specifically, I assume that the starting week of nonemployment and employer spells started in the month that precedes the survey reference week is evenly distributed across the weeks of the month, and use it to derive a weight function of weekly stocks of individuals with spell durations equal to one month, which I then add to weekly stocks of individuals in spells of duration equal to zero months to calculate the stocks of individuals in spells with duration less than five weeks.

Related literature. My paper is closely related to several recent papers estimating EE transitions using labor force survey data. First, Engbom (2021) and Donovan et al. (2022) estimate EE transition probabilities for some of the countries in my sample and over a similar time period. In general, those papers have a different focus than mine. Specifically, while they emphasize average cross-country differences in the levels of EE transitions, I also focus on their time variation, in particular their cyclical and low-frequency dynamics. Furthermore, they use either different data sources and/or different measurement approaches. The three approaches have different merits. Engbom (2021) measures annual EE rates for several European countries from 1991 until 2014 using microdata from the European Community Household Survey (ECHPS, 1994-2001), its successor, the European Union Statistics on Income and Living Conditions (EU-SILC, 2003-2014), the German Socio-Economic Panel (1991–2011) and the British Household Panel Survey (1991–2008). Those data sources are a closer counterpart to the US Panel Data on Income Dynamics (PSID), while the EULFS is modeled on the CPS. Consequently, the EULFS has larger monthly sample sizes and, as I show in this paper, can be used to measure monthly transitions at a monthly frequency. On the other hand, the ECHP/EU-

SILC are fully harmonized surveys, which is not necessarily the case for the EULFS and, put together, they allow Engbom (2021) to measure EE transitions for a larger set of countries (though not all countries in my sample) over a longer time period. Donovan et al. (2022) measure quarterly EE transitions using EULFS data. They cover more European countries (though not all of those in my sample) over a similar time period. The main difference pertains to the measurement approach. They measure EE transitions by linking individual observations across consecutive quarters, and combine them with employer spell durations.[1] Transition estimates based on duration and longitudinal data are each subject to potentially different sources of bias: duration estimates are exposed to recall bias, and longitudinal estimates to attrition bias.[2] Donovan et al. (2022) address potential attrition bias using a calibration approach, and I focus on short durations to reduce exposure to potential recall bias.[3] Setting those biases aside, the main advantage of my approach is that I measure monthly transitions, which are less exposed to potential time-aggregation bias. On the other hand, since the EULFS has a quarterly frequency, my time series are noisier, and require additional adjustments.

A second set of recent papers measure monthly EE transitions using labor force survey data from the United Kingdom (UK) (Postel-Vinay and Sepahsalari (2019)), Canada (Nakamura et al. (2020)) and the US (Fujita et al. (2021)). In general, my findings convey a similar picture to the one offered in those papers (the EE probability is large, accounts for a large fraction of hires and separations, and displays large procyclical variation) for several European countries, and bring additional evidence to the debate on the trend dynamics of labor market turnover. Last, a set of older papers estimate labor market aggregate transition probabilities among European countries. Those papers focus either on earlier time periods (Ridder and Van den Berg (2003) and Jolivet et al. (2006)) and/or transitions in and out of unemployment (Hobijn and Şahin (2009) and Elsby et al. (2013)).[4]

Implications and directions for future work. Arguably, the most influential evidence on EE mobility is based on the redesigned US CPS (Fallick and Fleischman (2004) and Fujita et al. (2021)). Relative to that evidence, the results in my paper highlight three important implications and directions for future work. First, my estimates indicate that the extent of employer-to-employer mobility varies substantially across countries, even among a sample of developed economies. Understanding what, if any, policies and other institutional factors may account for those differences seems especially important. A potential avenue in this direction is to study the effects of labor market policies on both nonemployment and EE reallocation

[1] They have longitudinal data because they either obtain microdata from the national statistical offices instead of Eurostat, implying that the legal restriction mentioned in the fifth paragraph of this Introduction does not apply, or they use EULFS household and individual identifiers which are consistent within the calendar year for some countries and years. See Footnote 6 for a more detailed explanation of this point.

[2] Both Engbom (2021)'s and my estimates are exposed to potential recall bias. Engbom (2021)'s rely on individuals' retrospectively reported labor market status over the past 12 months, while mine rely on individuals' recall of the starting date of their nonemployment/employer spell.

[3] Hairault et al. (2015) show evidence that recall error bias estimates of the job-finding and job-separation rates using data from the French Labor Force Survey. They show that the extent of recall bias is negligible for short recall periods (a couple of months), but increases substantially with the length of the recall period.

[4] Hobijn and Şahin (2009) also estimate the employer-separation probability, which is the sum of the employment-separation and the employer-change probabilities.

based on on-the-job search models (e.g. Postel-Vinay and Turon (2014)). Second, the evidence produced in this paper on the very large variation in EE mobility around recessions in European countries reinforces the notion that EE mobility is a prominent feature of business-cycle adjustment in the labor market. The data produced in this paper can be used to inform and discipline quantitative applications of business-cycle labor-market models with search on the job to European countries. Third, I find that the EE probability exhibits large low-frequency variation, indicating that average comparisons of EE mobility can be misleading, even among a relatively short period of 15 years. That variation seems disconnected from the business cycle, raising the question of what other forces drive EE dynamics (e.g. productivity dynamics, sectoral reallocation, etc.), including the possibility that undocumented changes in survey design may generate spurious variation (e.g. Fujita et al. (2021)).

Organization. Section 2 describes the EULFS data, the relevant survey questions, and the sample. Section 3 defines the objects of interest and develops the theory to measure them using EULFS cross-sectional data. Section 4 describes how I implement my measurement approach to estimate monthly transitions using EULFS data. Sections 5, 6, 7 and 8 describe the empirical results, and Section 9 concludes.

2 Data

The EULFS is a harmonized labor force survey comprising the majority of European countries and covering a relatively long time period. It is produced by Eurostat in collaboration with member-countries' statistical offices. Each country is responsible for designing and implementing the survey according to European regulations, while the Eurostat processes the data produced by member-countries and distributes the harmonized microdata to researchers.[5] Even though most countries' labor force surveys include a longitudinal dimension with a rotational structure, the EULFS is made available to researchers as a series of cross sections.[6]

The Eurostat makes the EULFS microdata available to researchers in yearly and quarterly extracts. The yearly extracts go further back in time (for some countries as far back as the 1980s), but they suffered several changes over time and the extent of cross-country harmonization is lower than in the quarterly extracts. Indeed, starting in the late 1990s and up until 2005 all countries adopted a redesigned survey, conducted quarterly, with interviews distributed

[5] See `https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey`. I use the November 2021 microdata release, which covers all available periods up to December 2020 for most countries.

[6] '*The EULFS is originally not designed as a panel, but most countries have a rotation scheme in place. The anonymised LFS microdata, however, 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.*' and '*it was decided not to allow the tracking of persons across successive sets of microdata for the time being. INTWAVE itself is delivered, but the household numbers (HHNUM) are randomized Eurostat (2021)* (p. 68). Readers who remember Footnote 1 may be confused at this stage. I was too when I first read Donovan et al. (2022). After talking to people familiar with EULFS data, I found out that the contradiction between what the Eurostat states in its official user guide and the content of the data has been known for some time. Notwithstanding, and as I have tried to argue in the paragraphs summarizing the related literature, my estimates, which do not rely on longitudinal identifiers, have some advantages relative to longitudinal estimates.

uniformly across all weeks of the quarter, and using a common conceptual and measurement framework. For these reasons, I use the quarterly extracts in my analysis. I further restrict the time dimension of each country's sample to periods in which all relevant variables are available, and when all the weeks in the calendar year are covered.[7]

2.1 Survey questions and variables

In the reference week civilian individuals are classified as either employed or nonemployed according to the International Labor Organization (ILO) definitions. Individuals are considered employed if they did any work, or did not work but had a job or business they were temporarily absent from, in the reference week. Therefore, in addition to employees, the stock of employed in the reference quarter includes unpaid family workers and the self-employed. All remaining civilian working-age individuals (15 to 74 years old) are classified as nonemployed. The EULFS asks nonemployed individuals if they had any previous work experience (EXISTPR) and, to those who respond affirmatively, asks the year (YEARPR) and month (MONTHPR) in which they last worked. I combine that information to calculate the duration of nonemployment (in months) for each nonemployed individual. Similarly, all employed individuals are asked the year and month in which they started working continuously for their current employer or as self-employed (YSTARTWK and MSTARTWK, respectively). I use that information to compute the duration of the spell with the current employer of all employed workers in the reference week.[8]

2.2 Sample selection

The EULFS microdata quarterly extracts include information on 31 countries. I select countries based on two criteria: a large economy (measured by GDP in international dollars in 2019) and availability of data prior to the 2008-09 financial crisis. My initial sample comprises the following 20 countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and the United Kingdom (UK).[9] From that sample I exclude France (the survey questionnaire was completely revised in 2013 implying a substantial break in the series

[7] The exception is Hungary. From 2001:q1 to 2005:q4 the Hungarian LFS only surveys one week in each month. This data structure can be easily accommodated within my measurement framework, so I include those time periods as well.

[8] As stated above, although the EULFS is structured around a common questionnaire, it is implemented by each member-country's national statistical office. This may imply that the text of the questionnaire does not exactly match the text stipulated in Eurostat's questionnaire. I inspected the text of each country's survey questionnaire, which are available online from Eurostat's webpage. For most countries, the questions match the concepts describe above. However, for some countries the text of the questions appears to imply some deviations from the concepts above. It is unclear to me to what extent these deviations are a consequence of translation into English, and whether or not in practice the exact concepts stipulated by the Eurostat are correctly implemented. In Borowczyk-Martins (2022) I display the text of the relevant questions for the earliest (usually 2005) and latest period (2019) for which questionnaires are available on Eurostat's webpage. In many cases I use Google Translate to perform the translation from the country's original language into English.

[9] Data for Switzerland starts in 2010:q1.

of short-duration employer stocks), the Netherlands (the question eliciting nonemployment duration refers exclusively to jobs with duration greater than one year), Norway (there are no valid answers to recover short-term nonemployment duration from 2010:m4 to 2012:m12), and Romania (the estimates of the employer-to-employer rate are systematically negative, which is not plausible). I also exclude Greece, Ireland and Slovakia, since there are many periods in which the number of available observations to estimate the stock of unemployed/nonemployed with short duration does not satisfy the reliability thresholds set by Eurostat. For the remaining countries, I exclude certain periods at the beginning of the sample when the extent of missing answers to the questions necessary to estimate individual nonemployment and/or employer spell durations is too great or the reliability thresholds are not satisfied. Table 1 provides a summary of the monthly sample size and time periods covered in my analysis.

Table 1: Description of the sample

Country	Acronym	Start month	End month	Sample size
Austria	AT	2005m7	2020m12	12,633
Belgium	BE	1999m1	2020m12	7,378
Czech Republic	CZ	2002m1	2020m12	16,447
Germany	DE	2005m1	2019m12	31,260
Denmark	DK	2001m1	2020m12	6,890
Spain	ES	1999m1	2020m12	42,111
Finland	FI	2003m1	2020m12	9,558
Hungary	HU	1999m1	2020m12	20,026
Italy	IT	2004m1	2020m12	42,414
Poland	PL	2000m1	2020m12	13,186
Portugal	PT	1998m1	2020m12	11,017
Sweden	SE	2005m10	2020m12	17,094
United Kingdom	UK	1999m3	2020m9	29,151

Notes: EULFS data. The column 'Sample size' reports the average monthly number of observations in 2007 with valid cross-sectional weight, labor force status and of the working age (between 15 and 74 years old).

3 Identification of hazard rates

In this section I describe an accounting framework linking the dynamics of employer and nonemployment stocks at different durations to hazard rates in and out of those stocks (my objects of interest). I follow the framework developed by Shimer (2012), and assume those hazard rates are the parameters of continuous-time Poisson processes governing worker mobility across employment and nonemployment, and across employers. I observe stocks of workers at discrete time periods of length equal to one month, which I index by t. I allow labor mobility to occur at a higher frequency than the month, and denote time elapsed within each month by $\tau \in [0, 1]$. Last, I assume hazard rates are constant within each month and ignore the dynamics of the working-age population (hence, all stocks are normalized by the size of the working-age population).

3.1 Hazard rates between nonemployment and employment

The point of departure of my analysis are the laws of motion of the stock of nonemployed workers at all durations ($n_{t+\tau}$) and at short duration ($n_t^s(\tau)$)

$$\dot{n}_{t+\tau} = e_{t+\tau} h_t^{EN} - n_{t+\tau} h_t^{NE} \tag{1}$$

$$\dot{n}_t^s(\tau) = e_{t+\tau} h_t^{EN} - n_t^s(\tau) h_t^{NE} \tag{2}$$

The stock of short-duration nonemployed counts individuals who are nonemployed at time $t+\tau$ and who were employed at some point in time $t' \in [t, t+\tau]$. At the beginning of each month ($\tau = 0$) the count of short-duration nonemployed is zero ($n_t^s(0) = 0$) and, by definition, at the end of each month ($\tau = 1$) that count is $n_t^s(1) \equiv n_{t+1}$.

Both stocks evolve according to the path of two flow hazard rates (the nonemployment-to-employment rate, h_t^{NE}, and the employment-to-nonemployment rate, h_t^{EN}) and the stock of employed workers, $e_{t+\tau}$. As shown by Shimer (2012), combining (1) and (2), and solving the resulting differential equation, delivers an expression for h_t^{NE} as a function of the observables n_t, n_{t+1} and n_{t+1}^s:

$$\exp(-h_t^{NE}) = \frac{n_{t+1} - n_{t+1}^s}{n_t}. \tag{3}$$

Intuitively, h_t^{NE} is identified by the fraction of nonemployed last month who are still nonemployed this month, which is simply the count of all nonemployed in the current month minus those who entered nonemployment during the month.

To identify h_t^{EN}, I follow Shimer (2012) and solve equation (1) forward one month to obtain an expression linking the stocks of nonemployed (n_{t+1} and n_t) and the two hazard rates (h_t^{NE} and h_t^{EN}):

$$n_{t+1} = \lambda_t^n \bar{n}_t + (1 - \lambda_t^n) n_t. \tag{4}$$

Note that $\lambda_t^n = 1 - \exp(-h_t^{EN} - h_t^{NE})$ denotes the rate of convergence to steady state and $\bar{n}_t = h_t^{EN}/(h_t^{NE} + h_t^{EN})$ the steady-state nonemployment rate. Given the value of h_t^{NE} determined by equation (3), I solve (4) for a unique value of h_t^{EN}.[10]

[10] As noted by Shimer (2012), 1) the right-hand side of (4) is strictly increasing in h^{NE}, and 2) the value of h_t^{EN} pinned down by equation (4) is robust to potential time-aggregation bias. In practice, the level of h_t^{NE} is about an order of magnitude smaller than the unemployment exit rate estimated in Shimer (2012). Therefore, the extent of time-aggregation bias in the estimate of h_t^{EN} obtained as $-\ln(1 - n_{t+1}^s/e_t)$ is small.

3.2 Employer-to-employer and employer-separation hazard rates

Similar to the stock of nonemployed, the law of motion of the stock of employed workers is driven by the hazard rates h_t^{NE} and h_t^{EN} according to the following equation:

$$\dot{e}_{t+\tau} = n_{t+\tau} h_t^{NE} - e_{t+\tau} h_t^{EN}. \tag{5}$$

Unlike the nonemployed, the EULFS does not record information on the duration of their employment spell. Instead, it records the duration of the spell with their current employer. With a slight abuse of notation, I denote the stock of workers in short-duration spells with their current employer by e_t^s. Its law of motion is given by the equation below:

$$\dot{e}_t^s(\tau) = n_{t+\tau} h_t^{NE} + \left(e_{t+\tau} - e_t^s(\tau)\right) h_t^{EE} - e_t^s(\tau) h_t^{EN}. \tag{6}$$

The dynamics of e_t^s depends, not only on the dynamics of the hazard rates between employment and nonemployment, but also on the dynamics of the hazard rate of changing employer, denoted h_t^{EE}, where EE is a shorthand for *employer-to-employer*. The stock of workers in short-duration employer spells decreases with separations to nonemployment ($-e_t^s(\tau) h_t^{EN}$), and it increases with hires from nonemployment ($n_{t+\tau} h_t^{NE}$) and employment ($(e_{t+\tau} - e_t^s(\tau)) h_t^{EE}$). Note that hires of employed who are already in short-duration employer spells at the beginning of the month do not affect the dynamics of $e_t^s(\tau)$, and are therefore subtracted from the stock of employed.

Subtracting (6) from (5), I get

$$\dot{e}_{t+\tau} - \dot{e}_t^s(\tau) = -(e_{t+\tau} - e_t^s(\tau))(h_t^{EN} + h_t^{EE}). \tag{7}$$

The solution to this differential equation is:

$$e_{t+\tau} - e_t^s(\tau) = -C \exp(-(h_t^{EN} + h_t^{EE})\tau). \tag{8}$$

where C is a constant. Evaluating (8) at $\tau = 0$ and $\tau = 1$, and using the definitions $e_t^s(0) = 0$ and $e_t^s(1) \equiv e_{t+1}^s$, I arrive at:

$$\frac{e_{t+1} - e_{t+1}^s}{e_t} = \exp(-h_t^{EN} - h_t^{EE}). \tag{9}$$

Given the value of h_t^{EN} pinned down by equation (4) and the observables e_t, e_{t+1} and e_{t+1}^s, equation (9) can be solved for a unique value of h_t^{EE}. Note that $h^{EE} + h^{EN} \equiv h^{ES}$, which is the employer-separation rate.

4 Estimation of hazard rates

To estimate the three hazard rates using the approach described in the previous section, I use EULFS data at a monthly frequency to estimate monthly transition rates. This raises three challenges. First, since the EULFS is designed to produce representative estimates of the population at a quarterly frequency, there is a concern with representativeness of monthly estimates. Second, I want to implement a consistent definition of short-duration spells at a monthly frequency. Third, I need to deal with missing answers to the questions necessary to compute individual durations. In the following subsections I state the three problems, and how I address each of them.

4.1 Transition estimates measured at a monthly frequency

Despite the quarterly frequency of the EULFS, it is straightforward to calculate transitions at a monthly frequency. I know the reference month of each interview (REM) as well as each individual's cross-sectional design weight (COEFF), so I can calculate the stocks of individuals in nonemployment and employer spells at all and short durations for every calendar month. However, there is a concern that estimates at a monhtly frequency are not representative of the population in the month. In general, I cannot provide an answer to that question. What I can do is compare my estimates to monthly estimates measured at a quarterly frequency. Specifically, I follow Elsby et al. (2013) and combine imputation with quarterly estimates of nonemployment stocks at all and short durations to estimate monthly hazards at a quarterly frequency. To illustrate this point, using that approach the monthly nonemployment-to-employment hazard rate in quarter t is equal to $-\ln(n_{t+1} - n^s_{t+1}) + 2/3\ln(n_{t+1}) + 1/3\ln(n_t)$, where t denotes a quarter instead of a month. Perhaps unsurprisingly, that approach produces estimates with very similar levels and time variation to the quarter averages of my monthly estimates.

The challenge posed by measuring monthly transitions at a monthly frequency is the extent of noise. In Table 1 I show that monthly samples are quite large, but, as readers familiar with the work of Elsby et al. (2013) will know, in European countries hazard rates are low, which implies that the number of individuals in short-duration spells is small and, as result, hazard rates estimates can be quite noisy. Elsby et al. (2013) cleverly address this problem by using stocks of individuals in spells of longer duration to measure monthly transition rates. This solution works well for countries with no state duration dependence, but it fails for countries that do. Although I do not formally test for state duration dependence, I find large differences in estimated hazard rates based on stocks of employed/nonemployed at different durations. Therefore, I estimate average transition hazards using only the hazard rates at the shortest duration spells (five weeks or less), since they are the least affected by potential duration dependence and are more directly comparable to US estimates.[11] In Section 6, I show that

[11]The problem of duration dependence is distinct from time aggregation. My estimates of h^{NE} and h^{ES} are not immune to time-aggregation bias, because in reality individuals can change labor market states and employer within the month, but that will not be adequately counted in the monthly stock of short-duration spells. However, given the size of measured transition hazards, at a monthly frequency the size of the bias is

a moving-average filter deals well with seasonal and very high-frequency variation, while also preserving cyclical variation.

4.2 The missing duration problem

At a monthly frequency the natural definition of a short-duration spell is less than five weeks, since any month has at most five weeks. However, the EULFS only allows one to obtain the spell duration in months.[12] The problem is then to determine how to best approximate the short-duration count based on the five weeks threshold using durations measured in months. I will explain exactly how that can be done in the next subsection. First, I describe how I calculate worker stocks in spells of durations measured in months in the presence of missing answers.

To calculate the duration (in months) of nonemployment and employer spells, I use information on the month and year of the start of those spells reported by survey respondents. For some nonemployed and employed individuals that information is missing. For employed individuals I use information on the month (MSTARTWK) and year (YSTARTWK) of the start of the employer spell and the survey's reference month (REM). If either MSTARTWK or YSTARTWK is missing, that duration is missing. For nonemployed individuals, I combine information on the existence of a previous employment experience (EXISTPR) with information on the month (MONTHPR) and year (YEARPR) of the end of the previous employment spell, and the survey's reference month. Individuals' nonemployment duration is missing if either EXISTPR, YEARPR or MONTHPR is missing.

As will become clear momentarily, to measure the short-duration stocks I need to calculate the stocks of individuals with duration equal to zero and one month. In practice, this entails classifying the nonemployed and employed with missing durations between those with a duration above or below one (zero) month(s). For the nonemployed, there are three groups of individuals with missing durations: 1) those with a missing answer to the question on whether they had a previous employment experience, 2) those for whom the year and/or month of their previous employment experience is missing, and 3) those who do not have a previous employment experience. The last group of individuals is the largest one, but it can be dealt with straightforwardly. According to equation (3), n^s_{t+1} measures newly nonemployed individuals, that is, individuals who were employed at time t and are nonemployed at time $t+1$. Therefore, I can classify all individuals with no previous employment experience among those with a long nonemployment duration. For the remaining individuals, in general, it is not possible to determine the length of their nonemployment spell.[13] In what concerns the employed, there

probably very small.

[12]Researchers using the CPS series of short-term unemployed (e.g. Shimer (2012)) do not face this problem. The CPS interviews all individuals in the same week of each month, and asks individuals explicitly if they have been unemployed for less than five weeks.

[13]There are a few exceptions, but they are quantitatively negligible. For example, for individuals for whom MONTHPR is missing, but not YEARPR, and REFYEAR-YEARPR $= 1$ and REM> 1, we can be sure they have a nonemployment duration longer than one month. Similarly, for individuals for whom MONTHPR is missing, but not YEARPR, and REFYEAR-YEARPR $= 0$ and REM< 2, we can be sure they have a

are only two sources of missing duration: either the month or the year of the current employer is missing.

For most countries and weeks in the final sample, the extent of missing nonemployment and employer durations is small (see Table 5 of Appendix B and Borowczyk-Martins (2022), where I display, for each country, the time series of the fraction of missing answers to all the questions necessary to measure employer and nonemployment spell durations). Therefore, to address this missing-data problem, I make a missing-completely-at-random (MCAR) assumption, which implies assuming that missing durations are independent of the true, unobserved durations. Under this assumption, I can calculate the number of nonemployed (employed with their current employer) with duration less than zero and one month as the product of the fraction of nonemployed (employed) with duration less than zero and one month among those with non-missing durations and the count of nonemployed (employed) in the reference week. To compute aggregate stocks from individual data, I use the cross-sectional weights (COEFF) produced by Eurostat and included in the EULFS microdata.

4.3 Stocks of individuals in short-duration spells

As a result of the procedure described in the previous subsection, at this stage I have, for each country, four time series with the count of individuals in nonemployment and employer spells of duration equal to zero and one month in every week of the year. As I now explain, in order to compute the monthly stocks of individuals in short-duration spells, I need to correct the series of stocks with duration equal to one month.

To fix ideas, with the EULFS data, the count of all nonemployed (employed with their employer) in a given month is simply the sum of all individuals in that state in each of the weeks that compose the month. A consistent measure of the short-duration stock should only count workers with durations less than or equal to five weeks in all the weeks that compose the month. Consequently, all individuals with duration equal to zero months should be counted in that stock. However, one may want to exclude interviewees with duration equal to one month. This is because, depending on the week in which they are interviewed in the month, some interviewees who report the start month of their spell as the previous month will likely have a duration longer than five weeks. To take one example, suppose I want to compute the stock of short-duration nonemployed in February 2020. February 2020 is composed of four weeks (week 6 to 9) and the previous month (January) is composed of five weeks (weeks 1 to 5). Clearly, all individuals who started their nonemployment spell in February 2020 have a nonemployment duration shorter than five weeks. Now, consider two nonemployed individuals in February 2020 who report as the starting date of their nonemployment spell January 2020, where one is interviewed in week 9 and the other in week 6. Their spell duration (in weeks) is unknown, but the individual interviewed in week 9 has a longer potential duration, and which is more likely to be longer than five weeks.

To deal with this problem consistently, I weigh stocks of individuals with duration equal

nonemployment duration shorter than one month.

to one month interviewed in different weeks differently, based on the assumption that the distribution of spells' starting week in the previous month is uniform. In the context of the example above, individuals interviewed in week 9 have been nonemployed for less than five weeks only if they became nonemployed in the last week of January. Under the assumption stated above, the weight of individuals in week 9 with a spell starting date January 2020 is then 1/5. By contrast, the weight given to individuals interviewed in week 6 with the same spell starting date is 1. More generally, the weight given to short-duration stocks equal to one month in each calendar week depends on the week number in the month (denoted wim) and the number of weeks in the past month (denoted #wpm). Specifically, the nonemployed short-duration count in each week is given by the function below:

$$n^s(\text{wim}, \#\text{wpm}) = \begin{cases} n^{\ell=0} + \sum_{\text{wim}=1}^{4} \left(n^{\ell=1} \times (1 - \text{wim})/\#\text{wpm}\right), \text{ if } \quad \#wpm = 4 \\ n^{\ell=0} + \sum_{\text{wim}=1}^{4} \left(n^{\ell=1} \times (0.8 - \text{wim})/\#\text{wpm}\right), \text{ if } \quad \#wpm = 5 \end{cases}$$

where $n^{\ell=0}$ and $n^{\ell=1}$ are the stock of nonemployed in the reference week with duration equal to zero and one month, respectively. The same formula applies to employer spells.

An alternative to the assumption that workers leave jobs and start new ones at a similar rate in different weeks of the month is to assume that *jobs always end in the last week of the month* and that *jobs with a new employer always start in the first week of the month.* Albeit extreme, this assumption seems plausible. Under that assumption, 1) the stock of nonemployed for less than five weeks is equal to the stock with duration less than or equal to one month, and 2) the stock of employed with their current employer for less than five weeks is equal to the stock with duration equal to zero months. To see this more clearly, take the stock of short-duration nonemployed. The survey questions elicit the calendar month of individuals' last employment spell (YEARPR and MONTHPR). Under the alternative assumption, an individual surveyed in any week of month t with YEARPR, MONTHPR equal to $t-1$, must have ended her latest employment spell in the last week of month $t-1$. However, this assumption has an implication that is strongly rejected by the data. Specifically, if it is true, any individual with a nonemployment spell equal to zero months, must have as its survey reference week the last week of month t — otherwise the person reports to be nonemployed before actually ending her current employment spell. But in the data, for all countries, there are many individuals with survey reference week in weeks 1, 2, 3 and 4 in the month and who report the end of their previous employment spell in the same month. Moreover, if I ignore this contradiction and compute the turnover probabilities under the alternative assumption, I find that they are much lower than my baseline estimates and systematically negative for most countries.[14] In sum, the data seem to favor my baseline assumption against the alternative assumption.

[14]A larger count of short-duration nonemployment spells raises h^{NE} and h^{EN}, and a smaller count of short-duration employer spells lowers h^{ES}. Put together, those changes imply a lower h^{EE}.

5 Average transition probabilities

In this section I describe average EE mobility in each sampled European country. In my analysis I describe *transition probabilities* instead of *hazard rates*. The former measure the probability that workers leave their current state to another one at least once during the frequency of observation, which is a month, and are denote by the letter p. I do this to facilitate comparisons with the previous literature.[15] To provide a more comprehensive reading of those estimates, I also describe countries' average mobility between nonemployment and employment, and I also show comparable estimates for the US. I use US gross flows estimates provided by the US Bureau of Labor Statistics to measure p^{EN} and p^{NE}, and US estimates of p^{EE} obtained by Fujita et al. (2021), which account for selection bias due to changes in the CPS Respondent Interview Policy.[16] Last, in an attempt to make more meaningful cross-country comparisons, I focus on a narrower period from 2006 to 2019. This allows me to cover all countries over the same time period. Given that most countries in the sample share common business-cycle shocks (viz. the Great Recession), this should facilitate the interpretation of those differences.

The two plots in Figure 1 show the average employer-to-employer probability on the vertical axis for the working-age sample (15 to 74 years old in EULFS data and 16 and over in the US). On the top plot, the horizontal axis shows the average employment-separation probability, whereas the bottom plot shows the average employment-finding probability. I distinguish countries according to their geography/institutions as indicated in Figure 1's legend. Focusing first on variation along the vertical axis, there is substantial cross-country variation in the average EE probability, ranging from 0.43 percent (Italy) to 3.54 percent (Sweden), with a large fraction of countries displaying rates around 1 percent. The very high value for Sweden is due to large EE probabilities among very young and older individuals. When calculated among prime-age individuals, the Swedish average EE probability drops to 2.2 percent (see Section C of the Appendix). Some interesting geographical patterns can be traced: the countries that exhibit the highest levels of employer-to-employer turnover are Nordic (Sweden and Denmark) and the US, and those with the lowest levels are Southern and Eastern European (Czech Republic, Hungary, Italy, Poland and Spain). In general, countries that are part of the same geographical region (and which share a similar economic and political history, as well as similar labor market institutions) show similar levels of employer-to-employer turnover. This is more clearly the case for Eastern European countries.

Focusing now on the relationship between average turnover across employers and between nonemployment and employment, the shape of both scatter plots in Figure 1 indicates that, on average, countries with high EE reallocation have high nonemployment reallocation, and that positive association is stronger between employment-finding and employer-to-employer probabilities. Comparing the markers along the horizontal axis on the two plots indicates a very

[15]There is a unique relationship between any turnover rate h_t and the corresponding probability p_t via the identity $p_t = 1 - \exp^{-h_t}$.

[16]BLS data is available at `https://www.bls.gov/webapps/legacy/cpsflowstab.htm`. I retrieved the time series of the EE probability from Giuseppe Moscarini's webpage (`https://campuspress.yale.edu/moscarini/data/`) in February 2022.

tight relationship between average p^{EN} and average p^{NE}, and reveals the greater extent of cross-country variation in p^{NE}. The most striking observation, however, is that in some countries the relative importance of EE reallocation is considerably lower than in others. The most prominent example is the US, which has average transition probabilities between employment and nonemployment that are several times greater than most other countries. Compared to Denmark, the US has a very similar EE probability, but both its transitions between employment and nonemployment are more than 2.5 times greater. Like the US, countries such as Italy and Spain exhibit a similar mix of low EE reallocation relative to nonemployment reallocation, albeit with much lower levels of all three transition probabilities.

One way to draw implications for labor market participants from the results in Figure 1 is to look at the ratio between p^{EE} and p^{EN}. In the context of the standard job-search model, that ratio measures the expected average number of job-offers during an employment spell, and quantifies the extent of employers' competition for workers.[17] According to that metric, the degree of competition for labor is much higher in most European countries compared to the US. The US labor market scores above the Italian and Spanish labor markets, but well below those of Nordic, Central and Eastern European countries.

Another approach to quantify the relative importance of employer-to-employer mobility in overall labor market turnover is to calculate EE flows as a fraction of hires and separations. Specifically, using the transition probability estimates and labor stocks, I compute EE flows as $EE_t = E_{t-1}p_t^{EE}$, hires as $H_t = EE_t + N_{t-1}p_t^{NE}$, and separations as $S_t = EE_t + E_{t-1}p_t^{EN}$.[18] Table 2 reports those numbers for the same period as Figure 1 (2006 to 2019). If we were to ask whether EE reallocation is quantitatively important in European labor markets, the answer given by those numbers would be a resounding yes. In all countries EE flows account for a substantial fraction of hires and separations, ranging from 25% in Italy and Spain to just above 60% in Denmark, Germany, Sweden and the UK.

In Subsection C of the Appendix I display counterparts to Figure 1 and Table 2 calculated on a sample of prime-age (25 to 59 years old) individuals for the European countries. Focusing on this narrower sample offers a simple way to control for potential cross-country differences in the extreme ends of the labor market (young and old workers). By and large, the main cross-country patterns are still present in the prime-age samples. The main difference concerns the level of the probabilities. Both the average employer-to-employer and the employment-separation probabilities are lower among prime-age workers, whereas the average employment-finding probability is higher.

[17] In that model, from the workers' perspective, employer changes are voluntary and utility-improving, whereas employment separations are involuntary and utility-reducing. Ridder and Van den Berg (2003) call that ratio the index of labor-market search frictions.

[18] To make this calculation, I filter both labor stocks and transition probabilities by a 12-month trailing moving average.

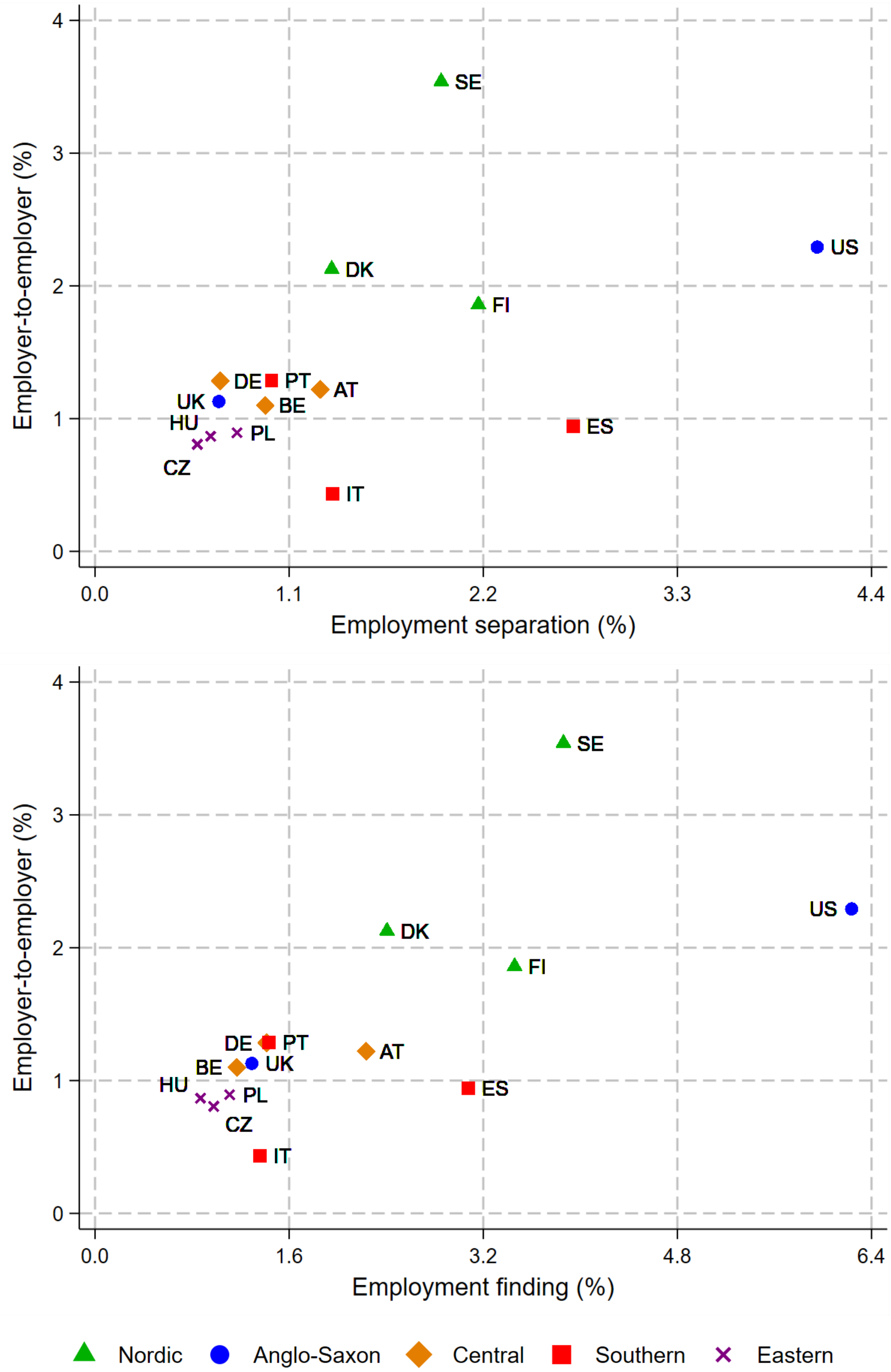

Figure 1: Average turnover probabilities

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 2006:1 to 2019:12. The markers in the plots denote sample averages of p^{EE}, p^{NE} and p^{EN} calculated in each country's time-series sample.

Table 2: Workers flows

Country	Sample averages			EE flows as share of	
	EE	EN	NE	Hires	Separations
Austria	0.77	0.81	0.82	48.26	48.62
Belgium	0.60	0.53	0.53	52.93	52.46
Czech Republic	0.49	0.35	0.38	56.39	58.43
Germany	0.81	0.45	0.51	61.44	64.42
Denmark	1.42	0.87	0.84	62.14	61.22
Spain	0.53	1.44	1.42	25.83	25.62
Finland	1.14	1.33	1.34	45.97	45.97
Hungary	0.46	0.35	0.40	53.49	56.91
Italy	0.22	0.67	0.67	24.43	24.09
Poland	0.49	0.44	0.50	49.65	52.50
Portugal	0.75	0.58	0.58	56.60	55.80
Sweden	2.35	1.30	1.30	64.40	64.34
United Kingdom	0.74	0.45	0.46	61.33	61.61
United States	1.38	2.46	2.24	38.14	35.90

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 2006:1 to 2019:12. Worker flows are reported as a fraction of the working-age population. All table entries are displayed in percent.

6 Cyclical variation

In this section I describe cyclical variation in the EE probability among working-age individuals for all the countries in my sample.[19] To better characterize the behavior of employer-to-employer mobility I also describe the behavior of transition probabilities between employment and nonemployment (p^{EN} and p^{NE}).[20] I cover at least two cyclical episodes for almost all countries: the Great and the Pandemic recessions and their preceding expansions.[21] Due to the Sovereign-debt crisis in the Eurozone, in some Eurozone countries the Great Recession exhibits a double dip (the first one roughly between late 2007 and 2009, and the second one between 2011 and 2013). To smooth seasonal and high-frequency variation in the monthly series, I use a 12-month trailing moving average filter. This approach is simple to implement and transparent, which is an important advantage when working with several time series for several countries. On the other hand, it entails losing one year of data for each country and it affects the timing of the series.[22] Even after filtering the raw data, some high-frequency variation remains in the time series of countries with smaller sample sizes, so in the plots I present the series as quarterly averages. The Pandemic Recession was very brief in many countries, which makes it difficult to track the dynamics of the transition probabilities with quarterly averages. Therefore, in Section D of the Appendix I report the time series at a monthly frequency.

Figures 2, 3 and 4 display time series of the employer-change, employment-separation and employment-finding probabilities, along with the unemployment rate, and the recession dates when available.[23,24] The time-series variation in countries' EE rates is substantial and, with the naked eye, one can see large variation around recessions, as well as low-frequency variation. I will describe the low-frequency variation in Section 8.

To summarize the large information contained in the time series displayed in Figure 2, 3 and 4, I organize it around general patterns that apply to most countries, which I them specify to the time-series behavior of specific countries. The first pattern pertains to the cyclicality of the EE probability.

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[19] In each European country, the prime-age and working-age time series exhibit very similar dynamics, so there is no great benefit in displaying both.

[20] Borowczyk-Martins and Pacini (2022) show that EULFS cross-sectional data do not allow one to estimate transition probabilities across employment, unemployment and nonparticipation using the standard classifications of labor market states defined by the International Labor Organization.

[21] For Germany 2020 data were not available at the time of writing.

[22] There are more sophisticated approaches to deal with seasonality, namely the X13-ARIMA algorithm popularized by the US Bureau of Labor Statistics. When I seasonally adjust the series using X13-ARIMA's standard specification, in most cases that variation (seasonal or high frequency) is not adequately removed. It may be possible to solve this issue by adjusting the series (i.e. before running the seasonal-adjustment step) for outliers and other sources of large high-frequency variation using external knowledge on the factors influencing the behavior of the different time series, but I have not pursued that possibility.

[23] I use the country-specific business-cycle dates proposed by the Economic Cycle Research Institute (ECRI) (`https://www.businesscycle.com/`) for European countries and the NBER's Business Cycle Dating Committee (`https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions`) for the US. For Eurozone countries not covered by the ECRI, I use the dates proposed by the Euro Area Business Cycle Network (`https://eabcn.org/dc/chronology-euro-area-business-cycles`).

[24] The time series of the unemployment rate is also smoothed by a 12-month trailing moving average.

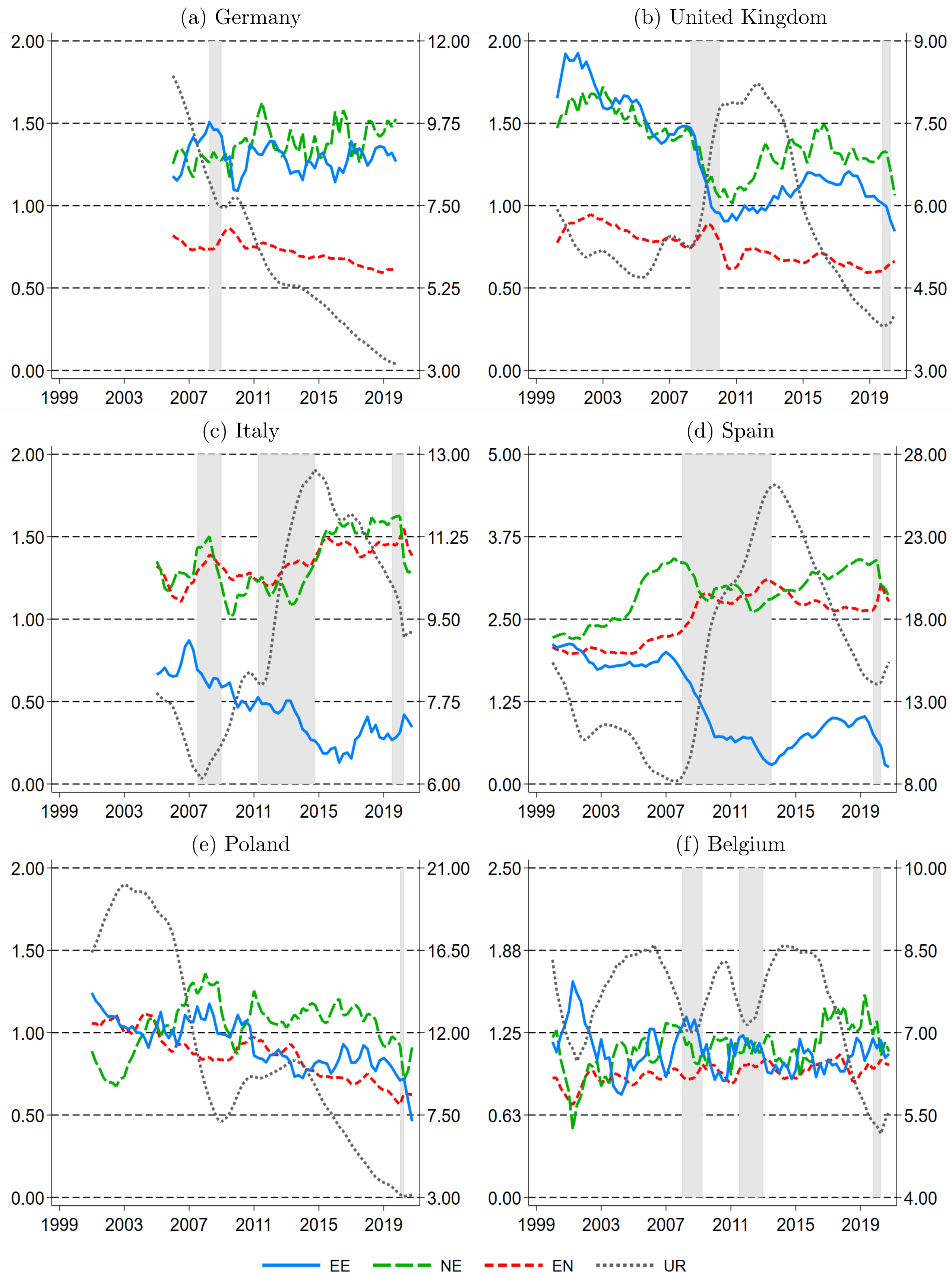

Figure 2: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 1999:q1 to 2020:q4 (start and end quarters differ across countries). p^{EE}, p^{NE} and p^{EN} are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

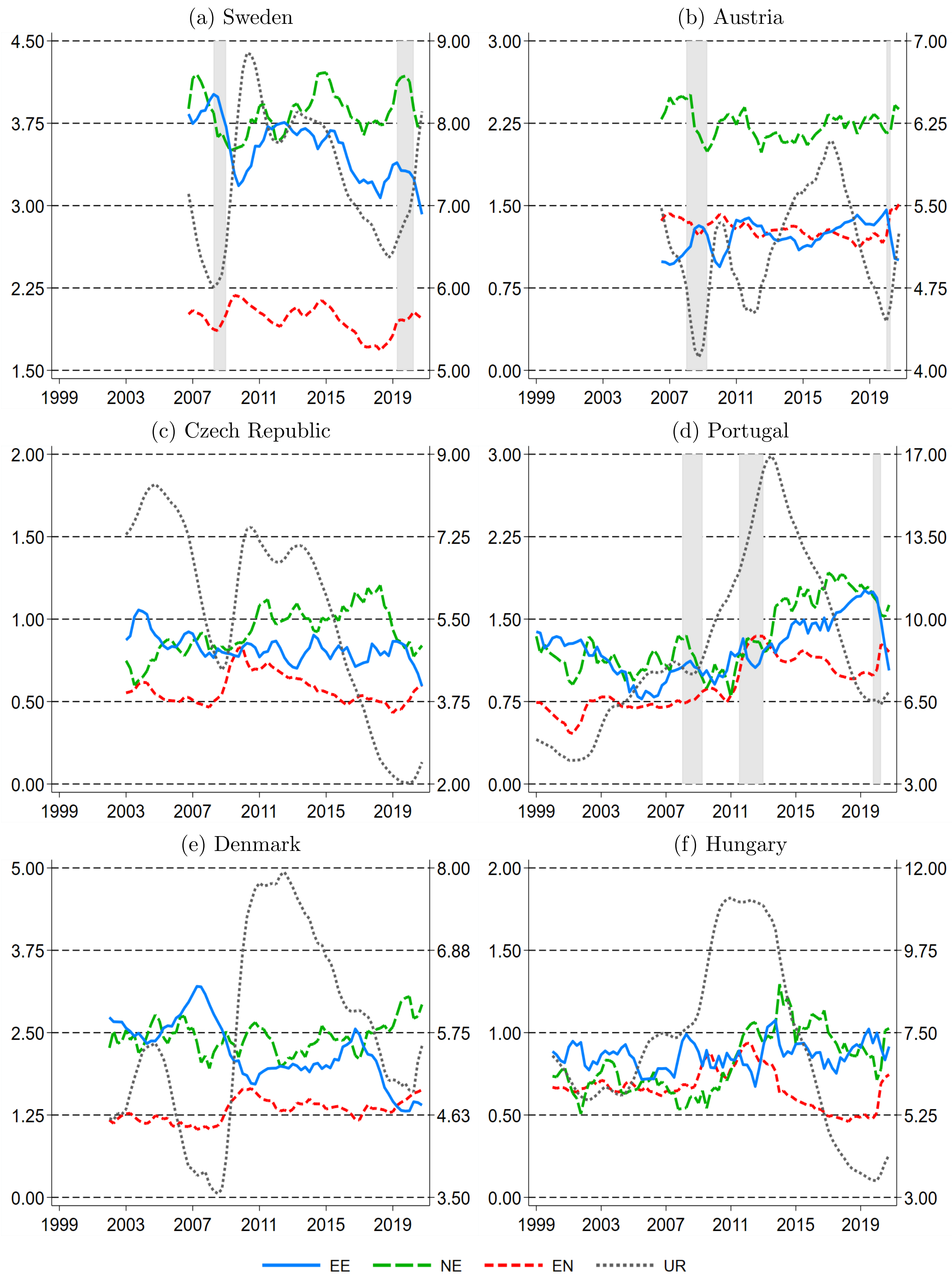

Figure 3: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 1999:q1 to 2020:q4 (start and end quarters differ across countries). p^{EE}, p^{NE} and p^{EN} are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

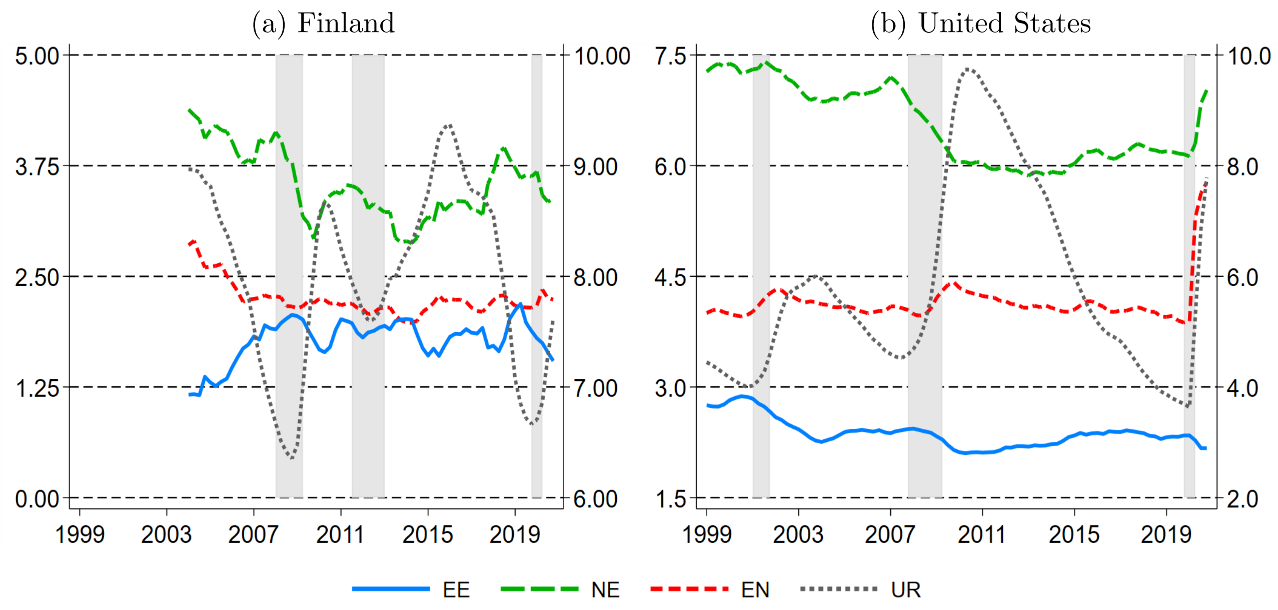

Figure 4: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 1999:q1 to 2020:q4 (start and end quarters differ across countries). p^{EE}, p^{NE} and p^{EN} are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

Pattern 1: The EE probability is procyclical.

P1.1. Inspection of the plots pertaining to European countries in Figures 2, 3 and 4 reveals large procyclical variation in the EE probability around recessions in almost all sampled countries. In most countries the EE probability drops around the time of the cyclical ramp-up in the unemployment rate, recovers as the unemployment rate declines, and grows steadily during expansions.

P1.2. The procyclicality of the EE probability around recessions is more clearly evident in countries that experienced several, rather moderate, cycles in the unemployment rate throughout the sample period (Austria, Belgium, Finland and Sweden). Since 2000 Belgium experienced three successive peaks and troughs in the unemployment rate (I am not counting the Pandemic Recession, which did not produce a large increase in the unemployment rate) that were all closely matched by shifts in the opposite direction in the EE probability. In Austria and Finland one can clearly see the EE probability comoving negatively with the unemployment rate as the latter moves up and down during the Great Recession and the Pandemic Recession. The last telling example is Germany, wherein the Great Recession produced almost no response in the unemployment rate, but led to a recessionary fall in the EE probability that is both large and displays the double-dip pattern that characterized the Great Recession in the Eurozone.

P1.3. The second group of countries experienced either large and/or persistent rises in unemployment during the Great Recession (Denmark, Italy, Spain, and the UK). Consistent with the procyclical behavior of the EE probability, in those countries one observes sharp and/or long-lasting falls in employer-to-employer mobility during the Great Recession. In all four countries the recovery in the EE probability in the Great Recession's aftermath is more sluggish compared to the employment-finding probability, although it seems to be partly driven by secular declines in EE mobility.

Given the richness of labor markets covered in the sample, there are naturally some exceptions and nuances to Pattern 1.

Exceptions to Pattern 1: In some countries the EE probability is not, or not always, procyclical.

E1.1. A first exception to Pattern 1 is offered by the Czech Republic. Since the early 2000s the EE probability fluctuates at a high frequency around a stable mean, but displays no comovement with the unemployment rate or the other labor market probabilities displayed in the plots, except during the Pandemic Recession. However, during the Great Recession, the directions of change in p^{EN} and the unemployment outflow probability (more on this in Section 7) are consistent with the conventional view: the sharp drop in the unemployment rate is accompanied by a spike in employment destruction (EN probability) and a fall in employment finding among the unemployed (UO probability). In contrast, the EE probability does not exhibit noticeable variation during that time window.

E1.2. A second exception is Hungary, where the large swing in the unemployment rate around the Great Recession finds no counterpart in movements in the EE probability.

E1.3. The third exception is given by Portugal during the Great Recession. Due to a strong upward trend in employer-to-employer mobility starting in 2006, it is difficult to discern with the naked eye the extent of cyclical variation around the Great Recession. In any case, on impact the drop in EE is very small compared to the extraordinary rise in the unemployment rate. On the other hand, during the Covid-19 recession the fall in the EE mobility is extraordinary.

E1.4. Last, inspecting the joint dynamics of the various series shows that, in certain periods, the behavior of p^{EE} does not comove negatively with the unemployment rate. Two striking examples are Denmark and Sweden in the expansion that precedes the Covid-19 crisis.

In an attempt to summarize in a few numbers the procyclical patterns visible in the plots, Table 3 reports the correlation coefficients between changes in the unemployment rate and changes in p^{EE}.[25] The resulting picture is closely aligned with the qualitative description in the preceding paragraphs. With the exception of the Czech Republic and Hungary, in all countries

[25] Because the time series are moving averages the correlation coefficients need to be interpreted with caution. On the other hand, the raw series of European countries time series contain large very high-frequency variation. Hence, after taking first-differences they are dominated by noise, and their correlation coefficients are basically zero.

the contemporaneous correlation coefficient is negative. In Poland and Portugal the coefficient is small and not statistically different from zero at 5% significance level.

Table 3: Correlation between unemployment and EE probability

Country	Coefficient	P-value	Obs.
Austria	-0.618	0.000	57
Belgium	-0.311	0.004	83
Czech Republic	0.041	0.737	71
Germany	-0.401	0.002	55
Denmark	-0.314	0.006	75
Spain	-0.560	0.000	83
Finland	-0.463	0.000	67
Hungary	0.015	0.891	83
Italy	-0.305	0.015	63
Poland	-0.165	0.146	79
Portugal	-0.136	0.208	87
Sweden	-0.506	0.000	56
United Kingdom	-0.468	0.000	81
United States	-0.665	0.000	87

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 1999:q1 to 2020:q4 (start and end quarters differ across countries). The table reports the country-specific contemporaneous correlation coefficient between first-differences of the time series of the unemployment rate and the employer-change probability. All time series are quarter averages of the monthly series smoothed by a 12-month trailing moving average.

Summary: To conclude, despite a few exceptions, the time-series evidence on the cyclical behavior of EE reallocation in European countries is closely aligned with US evidence documented by Fujita et al. (2021). Although it is difficult to precisely compare the volatility between the US and European countries due to the differences in survey design, compared to the US, EE mobility appears more volatile (especially around recessions) in most European countries. On the other hand, the cyclical response of the NE probability is relatively larger in the US compared to most European countries.

7 The recessionary drop in the EE and UO probabilities

Previously, I have established that, for a large set of countries, employer-to-employer mobility is large and comoves negatively with the unemployment rate. These observations are consistent with two features of aggregate models of the labor market featuring on-the-job search. First, employed workers search on the job. Two, firms vacancy-posting affects the job-finding prospects of both employed and nonemployed workers, and is affected by the composition of the pool of job searchers. Recent work in the US context explores the implications of the greater cyclicality of the job-finding probability of the unemployed relative to that of the employed for labor market dynamics (e.g. Moscarini and Postel-Vinay (2019), Eeckhout and Lindenlaub (2019), and Faberman et al. (forthcoming)). In this section, I try to inform those debates by assessing whether a similar pattern is present in European countries.

Figures 5, 6 and 7 track the dynamics of p^{EE} and of the probability that unemployed workers leave unemployment, or the unemployment outflow probability (denoted p^{UO}), around the Great Recession. I measure p^{UO} using stocks of short-term unemployed and equation (3).[26] Each time-series plot displays the two probabilities as a percentage of their peak value and tracks them for eight years, starting at the end of 2006 and ending at end of 2014. The solid line denotes p^{EE} and the dash line p^{UO}. In each plot the peak values for each time series are indicated by the respective vertical line. I select the 'peak' quarter for each series in order to clearly visualize the percentage adjustment in both series during this period.[27] Because the series are moving averages, the timing is not accurate.

As can be seen in Figure 7 b), in the US both p^{EE} and p^{UO} drop at the onset of the recession, but the percentage drop in p^{EE} is lower (a difference of about 20 percentage points). In what concerns the relative dynamics of p^{EE} and p^{UO} among European countries, there is no general pattern, as summarized in Pattern 2.

Pattern 2: In the Great Recession, the magnitude of the percentage fall in p^{EE} is either higher, smaller or similar to that of p^{UO}.

P2.1. In most countries where the EE probability is clearly procyclical (see P1 and E1 above) both p^{EE}*and* p^{UO} drop sharply around the start of the recession, and the recessionary drops in both series are fairly closely synchronized. In most of these countries, the percentage drop in the EE probability is much closer to that observed in the UO probability compared to the US, namely in Denmark, Italy, Spain, and the UK.

P2.2. Among countries with procyclical EE mobility, there are four (Austria, Belgium, Finland and Sweden) whose joint dynamics of the two transition probabilities are very similar to the US.

P2.3. In those countries where the EE probability is not procyclical during the Great Recession (Poland, Czech Republic, Portugal and Hungary), the unemployment outflow probability

[26] In general, stocks of unemployed measured in this way will not match those published by Eurostat and the Organization for Economic Cooperation and Development. My estimates are based on a different definition of short-term duration and use information on the year and month of the start of nonemployment spells (YEARPR and MONTHPR). Eurostat's estimates also use information contained in SEEKDUR, which reports job-search durations in months for nonemployed individuals. I do not use that information because the version of SEEKDUR available in the EULFS microdata does not allow me to calculate the number of individuals in unemployment spells of duration less than or equal to five weeks, since it is aggregated into three bins, where the bin with the lowest duration includes individuals whose search has not yet started or who have a duration of search less than six months. For the US, I use the BLS gross flows data to calculate: $p^{UO} = (UN_t + UE_t)/U_{t-1}$.

[27] This approach allows for the possibility that the recessionary drop in the two series is not synchronized, and not perfectly correlated with recession dates.

drops substantially at the onset of the recession.

P2.4. The clearest counter-example to the US is provided by Germany, where during the Great Recession the trough in p^{EE} is almost double that in p^{UO}.

Beyond the joint dynamics of p^{EE} and p^{UO}, visual inspection of Figures 5, 6 and 7 uncovers the large magnitude of the recessionary drops in the two probabilities in many European countries compared to the US. In the US, until 2010 the trough value is around 15 and 30 percentage points of the peak value, respectively for p^{EE} and p^{UO}. Among European countries over the same period, the peak-to-though changes in the two probabilities are usually larger. The large magnitudes can be partly explained by secular declines in EE mobility.

8 Low-frequency evolution

In Figures 2, 3 and 4 one observes clear trends in the EE probability over the sample period. The low-frequency evolution of labor market turnover probabilities is of great importance for the performance of an economy as argued for, and documented in, the debate on the decline in US labor market dynamism (see e.g. Davis and Haltiwanger (2015)). In this section I quantify the low-frequency evolution of the three labor market probabilities (p^{EE}, p^{NE} and p^{EN}) from the eve of the Great Recession (2007:q4) to the eve of the Pandemic recession (2019:q4).

The results are displayed in Table 4. The first two columns in each panel display the levels in the eve of each recession, whereas the third displays the percentage change across the two periods. Panel a) concerns employer-to-employer mobility. Running down the list of countries, one can observe that the evolution of p^{EE} varies dramatically. It increased very substantially in Portugal and Austria (although this seems to reflect the fact that in 2007:q4 in Austria p^{EE} is far from its pre-recessionary peak), while it fell considerably in Denmark, Spain, Italy, Poland, and the UK. On the other hand, in Belgium, Germany, the Czech Republic, Finland, and Hungary (the rather large positive value displayed in Table 4 reflects the fact that in 2007:q4 in Hungary p^{EE} is far from its pre-recessionary peak), just like in the US, the trend is largely flat. Inspection of panels b) and c) does not suggest any specific patterns of the joint evolution of p^{EE} and p^{NE}, or p^{EE} and p^{EN}. For example, Portugal experienced very large increases in all probabilities, whereas the opposite was the case in Poland. In Italy and Denmark the transitions between employment and nonemployment rose, while p^{EE} fell. Table 7 of the Appendix reports the same numbers for the prime-age sample. To sum up, the time series of p^{EE} displayed in Figures 2, 3 and 4 and summarized in Table 4 indicate that several European countries exhibit substantial low-frequency variation in EE mobility, while many others do not. In what concerns the direction of that evolution, there are no clear patterns across countries, and countries that exhibit similar EE long-run dynamics (e.g. downward trends) show more often than not rather different long-run dynamics in the other transition probabilities.

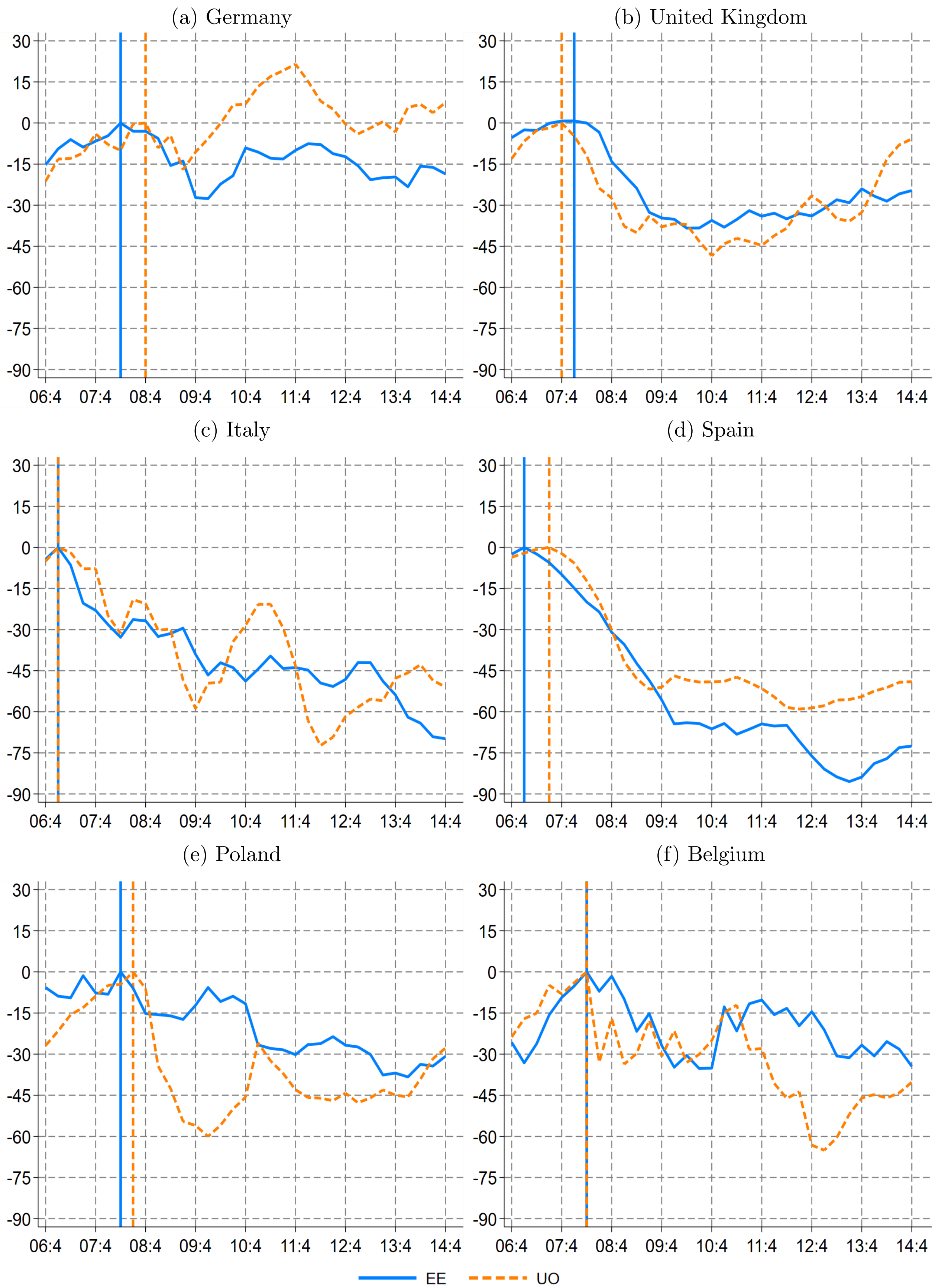

Figure 5: Employer-to-employer and unemployment outflow probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 2006:q4 to 2014:q4. Both probabilities (p^{EE} and p^{UO}) are denoted as the percentage of the value indicated by the corresponding vertical line. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

Figure 6: Employer-to-employer and unemployment outflow probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 2006:q4 to 2014:q4. Both probabilities (p^{EE} and p^{UO}) are denoted as the percentage of the value indicated by the corresponding vertical line. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

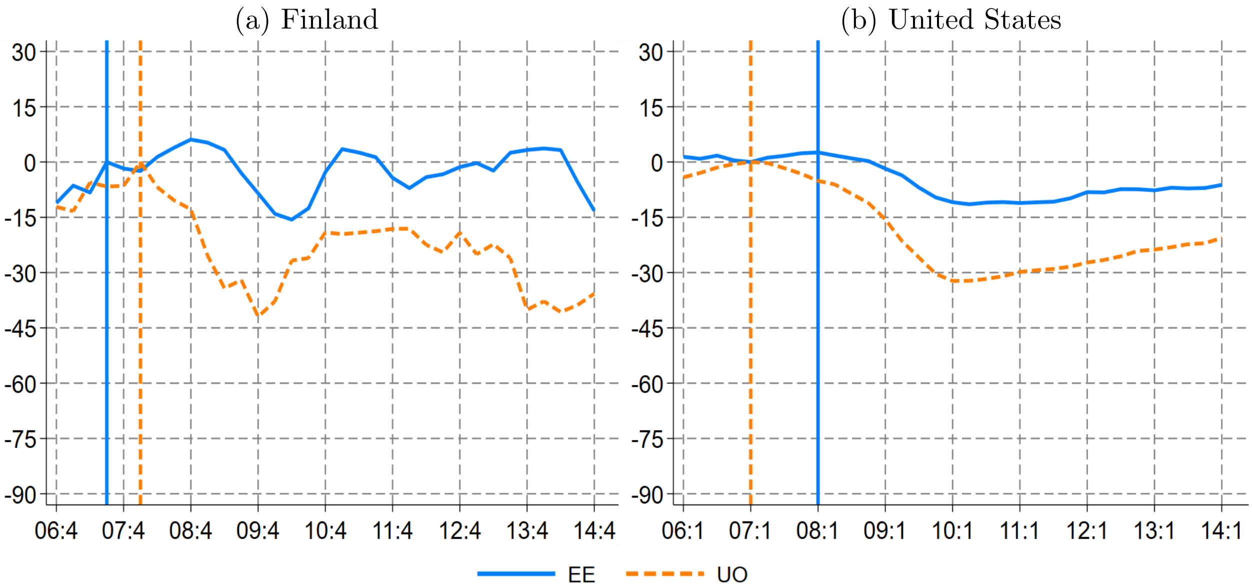

Figure 7: Employer-to-employer and unemployment outflow probabilities

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 2006:q4 to 2014:q4. Both probabilities (p^{EE} and p^{UO}) are denoted as the percentage of the value indicated by the corresponding vertical line. All series are quarter averages of the monthly series smoothed by a 12-month trailing moving average and expressed in percent.

Table 4: Low-frequency variation in transition probabilities

	EE			NE			EN		
Country	07:4	19:4	Change	07:4	19:4	Change	07:4	19:4	Change
Austria	1.0	1.4	34.7	2.5	2.2	-11.4	1.4	1.2	-16.2
Belgium	1.2	1.2	-2.9	1.3	1.2	-4.9	1.0	1.0	1.2
Czech Republic	0.8	0.8	8.5	0.9	0.8	-9.5	0.5	0.5	3.0
Germany	1.4	1.3	-9.9	1.3	1.5	16.4	0.7	0.6	-16.1
Denmark	3.1	1.3	-57.5	2.1	3.0	40.8	1.1	1.5	36.7
Spain	1.8	0.8	-57.7	3.4	3.4	-0.0	2.3	2.6	15.6
Finland	1.9	1.9	-1.6	4.0	3.6	-9.6	2.3	2.1	-5.1
Hungary	0.8	0.9	11.3	0.5	0.9	60.1	0.6	0.5	-26.0
Italy	0.7	0.3	-57.9	1.4	1.6	13.2	1.3	1.4	9.6
Poland	1.1	0.7	-31.1	1.3	1.0	-24.9	0.8	0.6	-29.7
Portugal	1.0	1.7	67.3	1.3	1.7	26.9	0.8	1.0	29.5
Sweden	3.9	3.3	-14.3	4.0	4.2	3.7	2.0	2.0	-0.9
United Kingdom	1.5	1.0	-31.6	1.4	1.3	-6.9	0.8	0.6	-20.8
United States	2.4	2.3	-3.6	6.9	6.2	-11.0	4.0	3.9	-4.3

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 2007:q4 – 2019:q4. In each panel the first two columns report the value of the quarter average of the monthly time series smoothed by a 12-month trailing moving average, and the value reported in column 'Change' corresponds to the percentage change between the value in column '2019:q4' and that in column '2007:q4'. All table entries are displayed in percent.

9 Conclusion

In this paper I provide a new set of monthly estimates of the employment-separation, employment-finding and the employer-change probabilities for 13 European countries over a period of 15-20 years. Two features of US EE mobility are present in most European labor markets: EE transitions are large and procyclical. On the other hand, the importance of EE mobility relative to nonemployment reallocation is, in general, higher in Europe vs the US. Last, the much debated decline in US labor market turnover observed in the first decade of the new century finds limited echo in the experience of the European countries in my sample.

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A Mathematical details

To expression for the nonemployment-to-employment hazard is obtained by subtracting (2) from (1), which gives:

$$\dot{n}_{t+\tau} - \dot{n}_t^s(\tau) = -n_{t+\tau}h_t^{NE} + n_t^s(\tau)h_t^{NE} = -h_t^{NE}\left(n_{t+\tau} - n_t^s(\tau)\right). \tag{10}$$

The general solution to (10) is:

$$n_{t+\tau} - n_t^s(\tau) = \exp(-\lambda^{NE}\tau)C. \tag{11}$$

Evaluating (11) at two particular solutions ($\tau = 0$ and $\tau = 1$), yields the following results. First, $n_t^s(0) = 0$ and $n_{t+0} - 0 = C$, or $C = n_t$. Second, $n_t^s(1) = n_{t+1}^{\leq 1}$ and $n_{t+1} - n_{t+1}^s = \exp(-\lambda^{NE})C$. Then, substituting in $C = n_t$ and rearranging gives $\frac{n_{t+1}-n_{t+1}^s}{n_t} = \exp(-h_t^{NE})$.

The expression for the employment-to-nonemployment hazard is obtained as follows. Since all stocks are normalized by the working-age population I can rewrite (1) as:

$$\dot{n}_{t+\tau} = (1 - n_{t+\tau})h_t^{EN} - n_{t+\tau}h_t^{NE} \Leftrightarrow \dot{n}_{t+\tau} + n_{t+\tau}\left(h_t^{EN} + h_t^{NE}\right) = h_t^{EN}$$

Solving this equation forwards one month, yields:

$$n_{t+\tau} = C\exp\left(-\tau(h_t^{EN} + h_t^{NE})\right) + \frac{h_t^{EN}}{h_t^{EN} + h_t^{NE}} \tag{12}$$

where $\bar{n}_t \equiv \frac{h_t^{EN}}{h_t^{EN}+h_t^{NE}}$ is the steady-state nonemployment rate. Evaluating (12) at $\tau = 0$, yields $n_t = C + \bar{n}_t \Leftrightarrow n_t - \bar{n}_t = C$. Substituting C in (12) and evaluating it at $\tau = 1$ yields $n_{t+1} = (n - \bar{n}_t)\exp\left(-(h_t^{EN} + h_t^{NE})\right) + \bar{n}_t \Leftrightarrow n_{t+1} = \lambda^n \bar{n}_t + n_t(1 - \lambda^n)$, where $\lambda^n = 1 - \exp\left(-(h_t^{EN} + h_t^{NE})\right)$.

B Missing durations

Table 5 reports percentile 95 of the fraction of month observations that have missing answers to the questions necessary to measure employer and nonemployment spell durations. In Panel a) 'Year', 'Month' and 'Total' denote, respectively, missing answers to YSTARTWK, MSTARTWK, or either. In Panel b) 'Year', 'Month', 'Total' denote, respectively, missing answers to YEARPR, MONTHPR, or either. 'Previous employment' refers to missing answers to the question of whether the nonemployed individual has a (previous) employment experience (EXISTPR).

Table 5: Fraction of missing answers to calculate durations

Country	a) Current employer spell				b) Nonemployment spell			
	Total	Year	Month		Total	Previous employment	Year	Month
Austria	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Belgium	1.4	1.2	0.3	5.7	2.4	2.8	0.6	0.5
Czech Republic	0.7	0.7	0.0	0.3	0.1	0.2	0.0	0.0
Germany	3.6	3.5	0.2	5.4	2.7	3.4	0.2	0.2
Denmark	2.7	1.1	2.7	10.0	2.6	8.9	0.0	0.0
Spain	0.0	0.0	0.0	0.1	0.0	0.0	0.1	0.1
Finland	0.7	0.7	0.2	15.0	14.0	1.2	0.2	0.1
Hungary	0.1	0.1	0.0	3.6	0.3	0.1	0.0	0.0
Italy	0.5	0.0	0.5	0.2	0.0	0.0	0.1	0.1
Poland	2.1	2.1	0.0	2.7	0.0	2.7	0.0	0.0
Portugal	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.0
Sweden	0.9	0.9	0.1	5.6	0.0	5.5	0.3	0.2
United Kingdom	1.2	1.1	0.1	1.2	0.6	0.7	0.1	0.1

Notes: EULFS data. Covereage: working-age sample from 1998:1 to 2019:12 (starting and end months differ across countries).

C Prime-age sample results

This section displays results presented in the main text but calculated on the prime-age (25 to 59 years old) sample.

Table 6: Workers flows

	Sample averages			EE flows as share of	
Country	EE	EN	NE	Hires	Separations
Austria	0.59	0.83	0.83	41.48	41.39
Belgium	0.57	0.51	0.50	53.06	52.24
Czech Republic	0.49	0.40	0.44	52.97	55.09
Germany	0.90	0.42	0.46	65.85	67.97
Denmark	1.57	0.72	0.67	69.69	67.92
Spain	0.55	1.62	1.60	24.51	24.24
Finland	1.02	1.02	1.01	50.17	49.78
Hungary	0.53	0.43	0.49	52.31	55.30
Italy	0.27	0.77	0.77	25.99	25.71
Poland	0.51	0.47	0.54	48.28	51.92
Portugal	0.83	0.62	0.62	57.17	56.73
Sweden	1.85	0.97	0.95	65.94	65.47
United Kingdom	0.67	0.41	0.43	60.74	61.48

Notes: Author's calculations based on EULFS data. Coverage: Prime-age sample, 2006:1 – 2019:12. Worker flows are reported as a fraction (in percent) of the prime-age population.

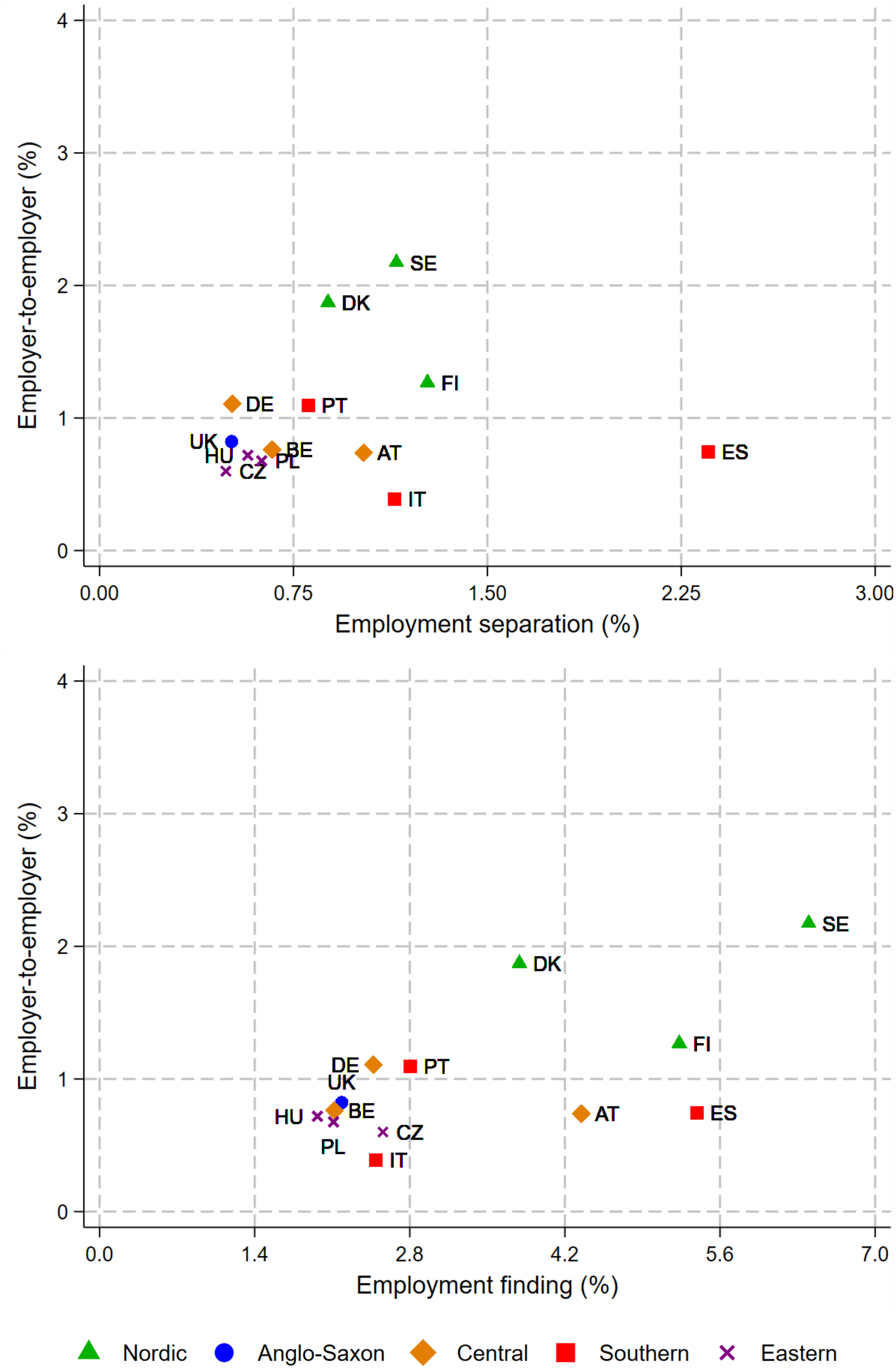

Figure 8: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data. Coverage: Prime-age sample from 2006:1 to 2019:12. The markers in the plots denote sample averages of p^{EE}, p^{NE} and p^{EN} calculated in each country's time-series sample.

Table 7: Long-run evolution of transition probabilities – Prime-age sample

	EE			NE			EN		
Country	07:4	19:4	Change	07:4	19:4	Change	07:4	19:4	Change
Austria	0.6	1.0	79.0	4.0	4.8	19.4	1.1	0.9	-18.0
Belgium	0.6	0.9	45.0	2.0	2.3	12.7	0.6	0.7	12.2
Czech Republic	0.6	0.7	10.3	1.9	2.5	28.8	0.4	0.4	-11.5
Germany	1.0	1.2	18.5	2.4	2.4	-2.2	0.6	0.4	-33.9
Denmark	2.3	1.3	-44.6	4.1	4.8	18.0	0.7	1.0	44.3
Spain	1.5	0.6	-59.9	5.4	6.5	21.5	1.8	2.3	24.8
Finland	1.1	1.5	36.4	5.5	5.8	5.9	1.3	1.3	-4.7
Hungary	0.6	0.9	58.0	1.5	1.8	20.9	0.5	0.3	-37.5
Italy	0.6	0.3	-59.0	2.3	3.0	29.1	0.9	1.2	28.6
Poland	0.8	0.6	-30.1	2.0	2.1	4.9	0.7	0.4	-41.1
Portugal	0.7	1.6	122.3	2.0	3.7	83.8	0.6	0.7	26.9
Sweden	2.2	2.2	-1.1	6.4	6.9	7.4	1.2	1.2	-5.2
United Kingdom	1.0	0.8	-15.9	2.2	2.4	11.8	0.6	0.4	-26.9

Notes: Author's calculations based on EULFS data. Coverage: Prime-age sample, 2007:q4 – 2019:q4. In each panel the first two columns report the value of the quarter average of the monthly time series smoothed by a 12-month trailing moving average, and the value reported in column 'Change' corresponds to the percentage change (in percent) between the value in column '2019:q4' and that in column '2007:q4'.

D Transition probabilities at a monthly frequency

Figures 10, 11 and 9 display monthly series of transition probabilities and the unemployment rate. The series are obtained by the author's calculations based on EULFS data. They cover the working-age sample from 1999:1 to 2020:12 (start and end months differ across countries). The transition probabilities between employment and nonemployment and across employers (EN, NE and EE) are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. The series are monthly and smoothed by a 12-month trailing moving average and are expressed in percent.

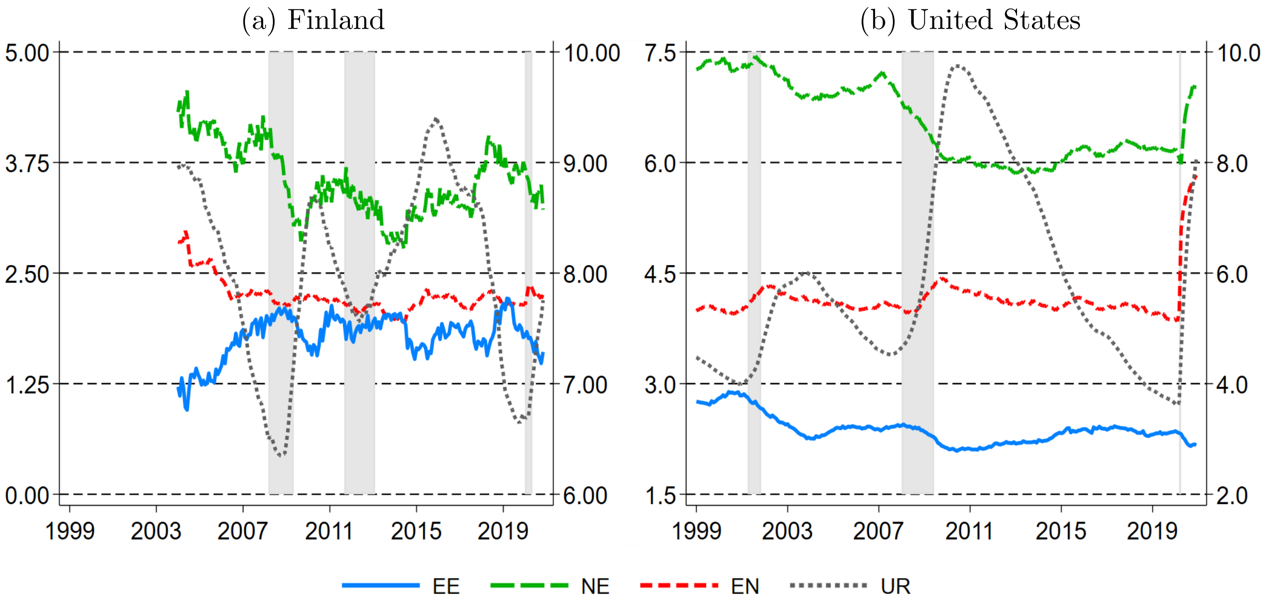

Figure 9: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data, US BLS gross flows data and the US EE probability estimated by Fujita et al. (2021). Coverage: Working-age sample from 1999:1 to 2020:12 (start and end months differ across countries). The transition probabilities between employment and nonemployment and across employers (EN, NE and EE) are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. The series are monthly and smoothed by a 12-month trailing moving average and are expressed in percent.

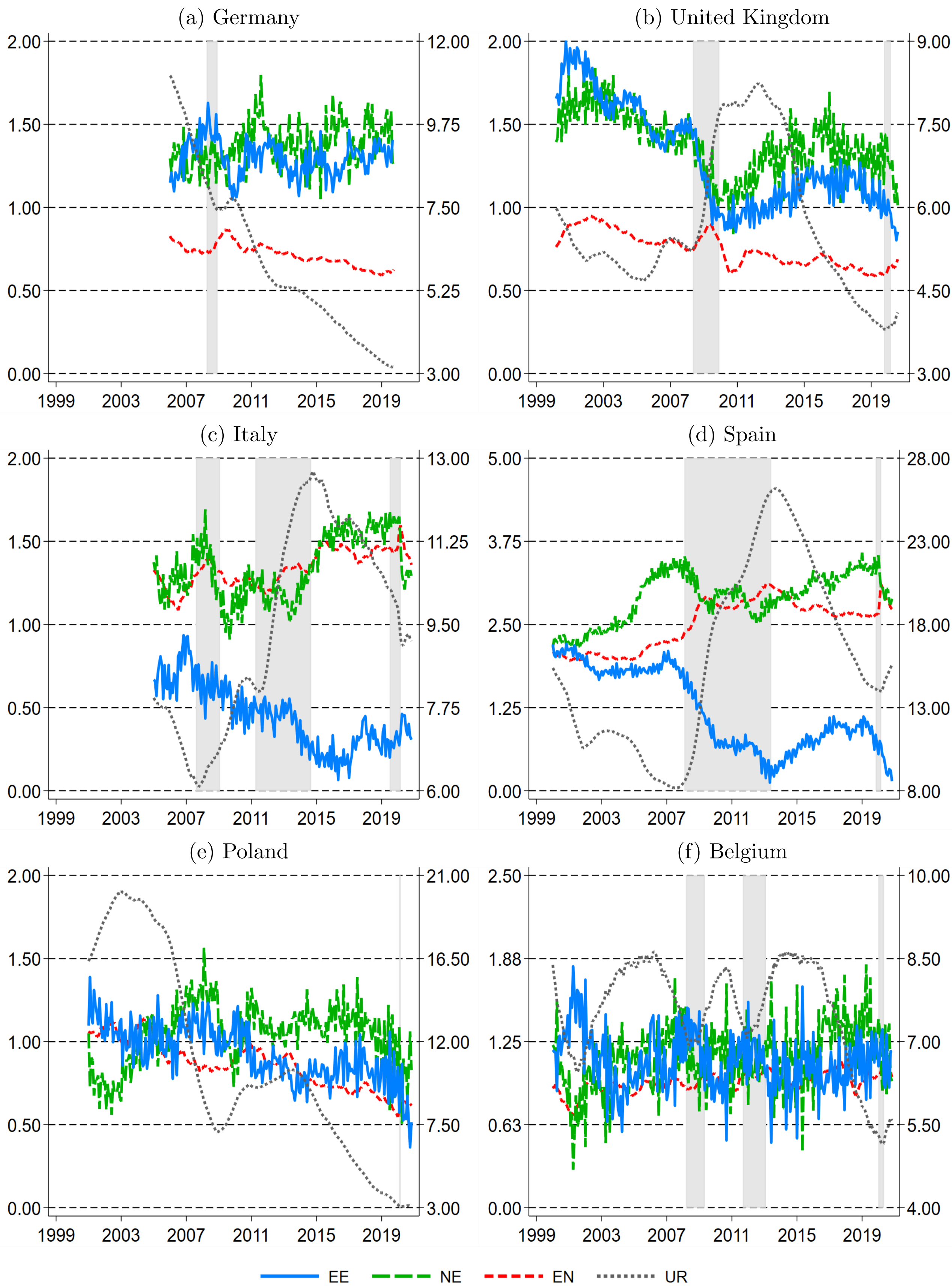

Figure 10: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 1999:1 to 2020:12 (start and end months differ across countries). p^{EE}, p^{NE} and p^{EN} are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. The series are monthly and smoothed by a 12-month trailing moving average and expressed in percent.

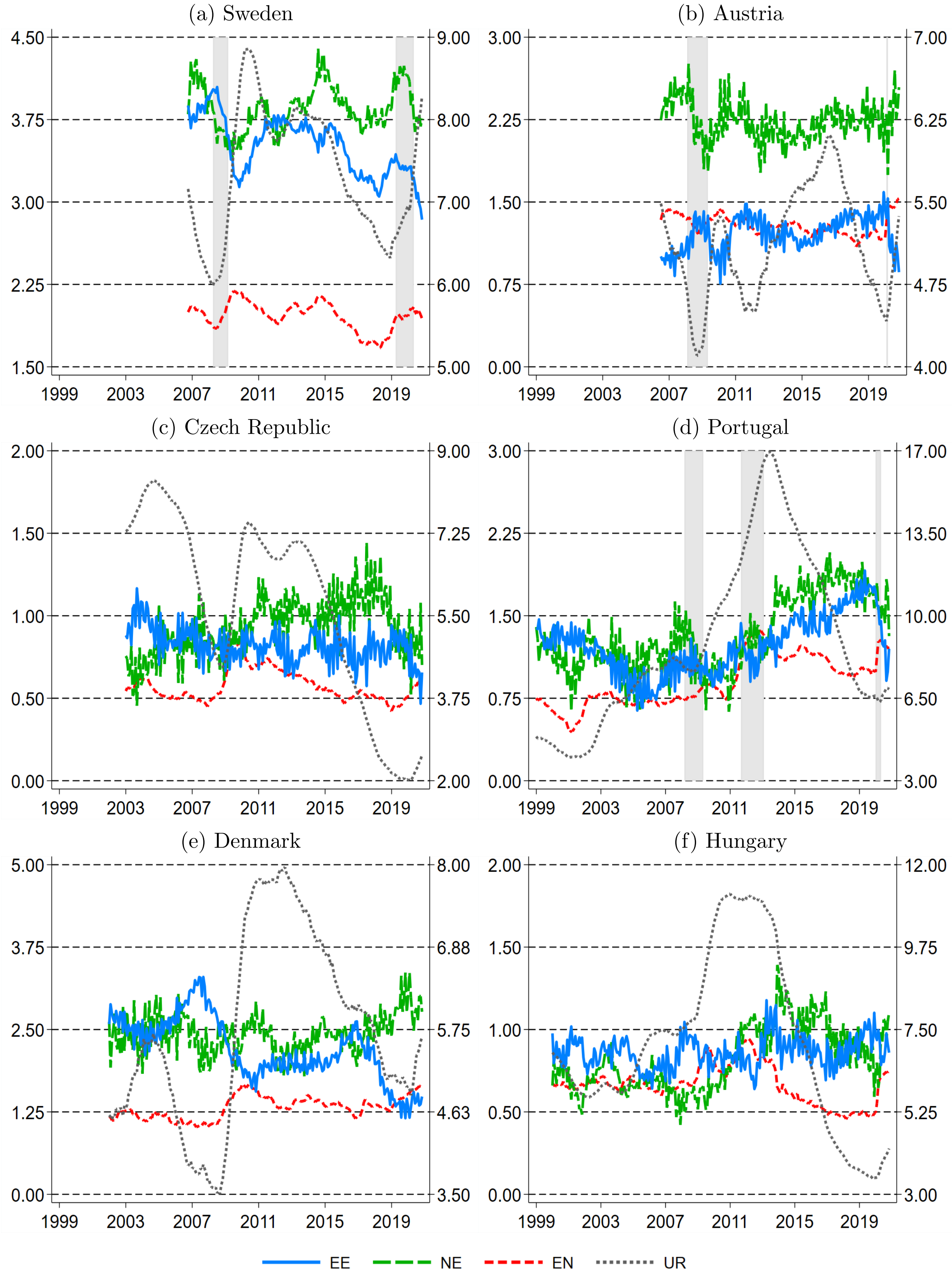

Figure 11: Employer-to-employer, employment finding and separation probabilities

Notes: Author's calculations based on EULFS data. Coverage: Working-age sample from 1999:1 to 2020:12 (start and end months differ across countries). p^{EE}, p^{NE} and p^{EN} are denoted on the left-hand side vertical axis and the unemployment rate (UR) on the right-hand side vertical axis. The series are monthly and smoothed by a 12-month trailing moving average and expressed in percent.