I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 17719

Employer-to-Employer Mobility and Wages in Europe and the United States

Daniel Borowczyk-Martins

FEBRUARY 2025

DISCUSSION PAPER SERIES

IZA DP No. 17719

Employer-to-Employer Mobility and Wages in Europe and the United States

Daniel Borowczyk-Martins
Copenhagen Business School and IZA

FEBRUARY 2025

ISSN: 2365-9793

ABSTRACT

Employer-to-Employer Mobility and Wages in Europe and the United States*

I produce novel evidence on worker reallocation across employers and between employment and nonemployment/unemployment for several European countries over the past two decades. I construct a dataset of monthly transition rates by developing a novel approach to measure them using cross-sectional data from the European Union Labor Force Survey. Transition rates exhibit similar cyclical patterns across countries, but their levels are persistently different. I compute an indicator of the pace of worker reallocation up the job ladder, and find that it varies substantially across countries, is pro-cyclical, and exhibits a systematic positive relationship with wage inflation.

JEL Classification: E24, E32, J63

Keywords: labor market flows, job ladder, business cycles, wage inflation, Phillips curve

Corresponding author:
Department of Economics
Copenhagen Business School
Porcelænshaven 16A
2000 Frederiksberg
Denmark

E-mail: dbm.eco@cbs.dk

* I am grateful to Annaïg Morin, Fabien Postel-Vinay, Grégory Jolivet, Idriss Fontaine, Peter Lihn Jørgensen, Philipp Grübener (discussant), Renato Faccini, and to seminar audiences at Aarhus University, Danmarks Nationalbank, the European Central Bank, the NorMac Symposium 2023, and the Bonn 2024 Workshop on Recent Developments in the Macroeconomics of the Labor Market for very useful comments. I received financial support from the Economic and Policy Research Network. Some results in this paper were included in the working paper 'Employer-to-employer Transitions in Europe'. The results and conclusions in this paper (including any potential errors) are my own, and do not represent the views of Eurostat or any of the national statistical offices who provided the data to Eurostat.

1 Introduction

The study of differences in unemployment rates and worker flows across Europe and the United States has been a fruitful avenue to advance our understanding of labor market behavior (see e.g. Blanchard and Portugal (2001) and Ljungqvist and Sargent (2008)). Much less is known about transatlantic variation in the rate at which workers change employers without an intervening non-employment spell. However, a vast array of theoretical and empirical work shows that reallocation across employers is an important determinant of key aggregate labor market outcomes, from the efficiency of labor allocation to the cyclical response of unemployment, to mention just a few (see the survey by Moscarini and Postel-Vinay (2018)). A current challenge facing US-Europe comparisons of employer-to-employer (EE) mobility is the lack of comparable, readily available, high-frequency measures for European countries. In this paper I fill that gap by measuring and analyzing time series of the aggregate EE monthly transition rate for 16 European countries over 20 years.

A common conceptual framework to interpret EE mobility is the job ladder: the notion that employers pay different wages, and that workers switch employers to realize wage gains. In canonical job-ladder models (e.g. Burdett (1978) and Burdett and Mortensen (1998)), EE mobility is a source of labor market power and a key driver of cross-sectional frictional wage inequality. In New-Keynesian business-cycle models featuring a job ladder, fluctuations in EE mobility are a crucial vehicle of the transmission of demand shocks to nominal wage growth (Moscarini and Postel-Vinay (2023) and Faccini and Melosi (2023)). The second contribution of this paper is to use the job-ladder framework to interpret variation in EE mobility. I find that average differences across countries in mobility rates are indicative of significant cross-country variation in the pace at which workers climb up the job ladder. I also show that the joint observation (common in my sample of countries) of a procyclical EE mobility rate and countercyclical employment-separation rate imply strong procyclicality in an indicator of the pace of reallocation up the job ladder. Consistent with the notion of a cyclical job ladder (Moscarini and Postel-Vinay (2018)), that indicator exhibits a strong positive relationship with wage inflation.

I first show how to obtain measurements of aggregate EE mobility for European countries that are comparable to existing US measures based on the Current Population Survey (CPS). My data source is the European Union Labor Force Survey (EULFS), a data product of the European Union's statistical office (Eurostat). Like the CPS, the EULFS relies on a large rotating sample, is conducted at a high frequency, and is very easily accessible by researchers. The EULFS is the harmonized version of European countries' national labor force surveys that are used to measure official labor market indicators like the unemployment rate. However, due to legal constraints (detailed in Footnote 12), it poses a significant challenge to measure labor market transitions. Even though the national labor force surveys used to construct the EULFS have a longitudinal dimension, Eurostat is not allowed to reveal the panel dimension of the data. Instead, the microdata for each country are released as time series of cross sections. Consequently, the standard method to measure transitions by linking individual observations of labor market state across consecutive periods is not applicable to EULFS data.[1]

To tackle that problem, I use cross-sectional information on individuals' employer and nonemployment spell durations that became available after the EULFS redesign implemented in the early 2000s in all countries. I develop a continuous-time measurement framework that expresses transition rates as functions of stocks of workers in nonemployment and employment in spells of different duration. I show that to measure the transition rate across employers, I first need to measure the transition rates between nonemployment and employment. To enrich my analysis I also measure the transition rates between unemployment and employment using data on stocks of unemployed in spells of different duration. The second distinctive feature of my approach is that I obtain monthly transition rates for European countries that are directly comparable to US monthly transition rates based on the CPS. It is not possible to measure monthly transitions using the longitudinal approach, since EULFS individual observations are spaced three months apart.

Having obtained measurements of transition probabilities for European countries, I combine them with CPS US data and the adjusted series of the US EE probability produced by Fujita et al. (2024). I start by comparing the average values of the turnover probabilities across the European countries in my sample and the US over a common period. I find substantial variation in the levels of all transition probabilities. The majority of European countries display EE probabilities around 1 percent, whereas in the US and some Nordic countries that value is closer to 2 percent. Second, I document variation in relative EE mobility, the ratio of the probabilities that an employed worker moves to another employer vs to nonemployment, p^{EE}/p^{EN}, or alternatively, p^{EE}/p^{EU}, where U stands for unemployment. Cross-country variation in relative EE mobility is large, and the US exhibits relatively low levels. The average US employed worker is more likely to move to nonemployment than to another employer, whereas in many European

[1] To be completely accurate, this statement requires a few qualifications. See the third paragraph of Section OA.1 of the Online Appendix. See also Borowczyk-Martins and Pacini (2024) for a formal analysis.

countries the average employed worker is 50% more likely to move to another employer vs to nonemployment. The patterns are similar when using the employment separation rate to unemployment. The next set of descriptive results concerns time variation in EE mobility within each country. Despite the presence of low-frequency variation in the time series of the EE probability of some European countries, cross-country differences in the levels of EE mobility persist over time. Like in the US, in most European countries the EE probability exhibits a procyclical pattern. Last, the patterns of comovement between the EE probability and the other transition probabilities also exhibit common patterns across countries: the EE probability is negatively correlated with the separation probability from employment to nonemployment/unemployment and, in some countries, it is also positively correlated with the transition probability from unemployment to employment.

To interpret my descriptive evidence, I use Burdett (1978)'s job-ladder model. This framework describes how workers receiving job-offers while employed and unemployed, and job-destruction shocks while employed, move up a (fixed) wage-offer distribution (the job ladder). A key insight from this framework is that observed EE mobility is linked to the level of employment separations. Specifically, if the probability to separate from employment is high, more workers occupy the lower rungs of the job ladder, where they are more likely to accept job offers, which raises the level of EE mobility. Hence, to properly gauge the ability of workers to reach the upper rungs of the job ladder, one must account for the size of the employment-separation rate. To do so, I use my transition rate estimates to compute the ratio of two parameters of the job-ladder model: the job-offer and job-destruction arrival rates of the employed. I label this quantity *the job-ladder reallocation index*. It measures the number of job offers received during an employment spell of average duration, governs workers' ability to earn higher wages (or labor market power) and, in a calibrated version of the model, is the main determinant of frictional wage dispersion (i.e. the ratio of the average wage to the minimum wage). I find substantial cross-country variation in the job-ladder reallocation index: the US, Spain and Italy exhibit the lowest levels, about an order of magnitude lower than the values of Germany, Sweden and the United Kingdom (UK). Regarding time variation in EE mobility, the job-ladder model highlights that strong countercylicality of the employment-separation rate damps the recessionary drop in the EE transition rate and, consequently, the evolution of the job-offer arrival rate of the employed tracks better the cyclical dynamics in opportunities to climb up the job ladder. That prediction is largely confirmed. The cyclical comovement of the job-offer arrival rate of the employed with the unemployment rate and the transition rate from unemployment to employment is stronger and more systematic across countries than that of the EE probability.

Last, I investigate the implications of the procyclicality of the job-ladder reallocation index for the behavior of nominal wage growth. The unemployment rate is usually seen as the main measure of labor market slack and the key driver of wage and price inflation. In recent years, most prominently in the work of Giuseppe Moscarini and Fabien Postel-Vinay, a richer view based on the notion of a cyclical job ladder has been proposed (see e.g Moscarini and Postel-Vinay (2013), Moscarini and Postel-Vinay (2018) and Moscarini and Postel-Vinay (2023)). According to that view, EE mobility is a key channel of the transmission of labor demand shocks to wages. While those models offer a broader and richer theory, the basic insight can be gleaned from a simple extension of the canonical wage-posting model by Burdett and Mortensen (1998), as shown by Moscarini and Postel-Vinay (2016). Put simply, positive shocks to aggregate productivity lead to an increase in the job-ladder reallocation index (via changes in the job-offer and job-destruction rates), thereby raising wage competition (or upward pressure on wages). That insight motivates an alternative specification of the empirical wage Phillips curve, where the job-ladder reallocation index, rather than the unemployment rate, drives nominal wage growth. I find evidence in support of the cyclical job ladder. Country-specific regressions of wage inflation on the job-ladder reallocation index deliver coefficients that are positive, large and statistically significant in the US and in almost all European countries, and robust to the inclusion of lagged price inflation.

Related literature. A few papers measure transition rates for European countries using other data sources and/or a different measurement framework (Jolivet et al. (2006), Engbom (2021), Donovan et al. (2023a) and Donovan et al. (2023b)). I propose a novel approach that extends Shimer (2012)'s analytical framework and uses spell duration data available in the EUFLS. Furthermore, compared to existing papers, mine is the only one that satisfies simultaneously three desirable features. First, it produces estimates for a large set of European countries over a long time period that are directly comparable to US CPS monthly estimates. Second, it delivers quarterly time series of monthly EE rates covering all months of the calendar year. Third, it relies on microdata that is very easily accessible by researchers and released yearly by Eurostat on an on-going basis, allowing my results to be examined, improved and extended as more data becomes available.[2] I provide a detailed description of the alternative estimates available in the literature in Section 2.5.

The analysis of my novel estimates of transition rates allows me to establish

[2]The data are available on my personal webpage.

findings that are new to the literature. First, there is an extensive literature documenting differences in the levels of worker turnover rates across countries and their relationship to labor market performance (see e.g. Elsby et al. (2013) and Bertola and Rogerson (1997)). My contribution is to document large differences across countries in a different outcome (relative EE mobility), which is informative about cross-country variation in the composition of employer separations. I show that, consistent with the conventional wisdom, the US exhibits higher reallocation between employment and nonemployment/unemployment compared to the average European country. However, I also uncover a new fact: the US displays much lower relative EE mobility compared to the average European country. Furthermore, similar to papers estimating job-search models using transition data on European countries and the US (Ridder and Van den Berg (2003) and Jolivet et al. (2006)), I use my estimates to compute the job-ladder reallocation index, a measure of labor market power in the job-ladder model. Compared to those papers, my analysis covers a more recent and longer time period and a larger set of countries.

Second, my findings based on time variation in EE mobility contribute to an empirical literature analyzing monthly time series of EE mobility based on labor force survey data for a single country (see Postel-Vinay and Sepahsalari (2023), Nakamura et al. (2020) and Fujita et al. (2024)). I extend those analyses to a large set of European countries. I go beyond that literature by showing that 1) countercyclical fluctuations in the transition rate from employment to nonemployment mute the procyclicality of EE mobility in some countries, and 2) by computing quarterly time series of the monthly job-offer arrival rate of the employed and showing that its procyclical behavior is stronger and more systematic across countries than the raw EE probability. Third, there is an empirical literature that uses US data and measures of EE mobility as an alternative/complement to the unemployment rate to quantify aggregate labor-market slack and its predictive power for fluctuations in wage and price inflation (see e.g. Moscarini and Postel-Vinay (2016), Karahan et al. (2017) and Moscarini and Postel-Vinay (2023)). I consider a different indicator (the job-ladder reallocation index) and show that it displays a strong positive comovement with wage inflation in the US and most European countries.[3]

Organization. Section 2 describes how I measure transition rates using EULFS data and assesses the validity of my measurements. Section 3 presents the data and my sample selections. Section 4 reports novel empirical evidence on EE mobility in Europe and differences relative to the US. Section 5 interprets the variation in my

[3] Jolivet (2009) estimates a similar indicator at a monthly frequency using transition and wage data from the US CPS between 1996 and 2006, but he does not relate it to the dynamics of wage inflation.

transition rates data using the job-ladder model. Section 6 concludes. An Appendix and an Online Appendix (OA) contain additional details and results.

2 Measurement and validation

In this section I first describe the analytical framework underlying my measurement of transition rates. Next, I briefly mention the challenges to implement that framework on EULFS cross-sectional data. Section A.1 of the Appendix complements Subsection 2.3 by providing a more detailed description of the implementation of my measurement approach. In Subsection 2.4 I assess the validity of my transition rates measurements. Last, Subsection 2.5 compares my measurement approach and estimates with existing alternatives in the literature.

2.1 Accounting framework

I develop a framework linking the dynamics of worker stocks at different durations to transition rates in and out of those stocks. I assume those transition rates are the parameters of continuous-time Poisson processes governing worker mobility across employment and nonemployment, and across employers. In the EULFS microdata I observe those stocks at a monthly frequency, denoted t. I allow labor mobility to occur at a higher frequency than the month, but assume transition rates are constant within each month, and ignore the dynamics of the working-age population.[4]

The law of motion of the stock of nonemployed (n_t) is given by the following equation:

$$\frac{dn}{dt} = e_t h_t^{EN} - n_t h_t^{NE}, \tag{1}$$

where e_t is the stock of employed, and h^{NE} and h^{EN} are the transition rates between nonemployment and employment. Solving Equation (1) forwards one month, delivers an equation expressing the nonemployment stock as a function of its lag and the two nonemployment transition rates:

$$n_{t+1} = \lambda_t^n \bar{n}_t + (1 - \lambda_t^n) n_t. \tag{2}$$

$\lambda_t^n = 1 - \exp(-h_t^{EN} - h_t^{NE})$ denotes the rate of convergence to steady state and $\bar{n}_t = h_t^{EN}/(h_t^{NE} + h_t^{EN})$ is the steady-state nonemployment rate.

The stock of nonemployed for less than one month at the beginning of next period $(t+1)$ counts individuals who were previously employed and have become

[4] All stocks are normalized by the size of working-age population.

nonemployed during the course of the current month (t), i.e. $n_{t+1}^{<1} = e_t p_t^{EN}$. Note that p_t^{EN} is a probability, i.e. the discrete-time counterpart to h_t^{EN}, since $p^{EN} = 1 - \exp(-h^{EN})$, and measures the likelihood that an employed worker moves to nonemployment at least once during the month. The stock of nonemployed for less than one month is related to the change in the nonemployment stock (Δn_{t+1}) by the following accounting equation:

$$\Delta n_{t+1} = n_{t+1}^{<1} - n_t p_t^{NE}. \tag{3}$$

Substituting in the expression of p^{NE} and rearranging gives an expression for h^{NE} as a function of observable nonemployment stocks:

$$\exp(-h_t^{NE}) = \frac{n_{t+1} - n_{t+1}^{<1}}{n_t}. \tag{4}$$

Given the value of h_t^{NE}, Equation (2) can be solved for a unique value of h_t^{EN}.[5]

The EULFS records the duration of individual spells with the current employer (tenure). With a slight abuse of notation, I denote the stock of employed with tenure less than one month at the beginning of next period by $e_{t+1}^{<1}$. It counts individuals who have become employed with their present employer within the current month. By definition, $e_{t+1}^{<1} = n_t p_t^{NE} + e_t p_t^{EE}$, where p_t^{EE} is the probability to change employers (EE is a shorthand for *employer-to-employer*). Starting from the accounting equation describing the evolution of the stock of employed:

$$\Delta e_{t+1} = n_t p_t^{NE} - e_t p_t^{EN}, \tag{5}$$

adding and subtracting to the right-hand side of the equation the count of employed workers who changed employer during the month ($p_t^{EE} e_t$), and rearranging yields:

$$\Delta e_{t+1} = n_t p_t^{NE} + e_t p_t^{EE} - e_t(p_t^{EN} + p_t^{EE}). \tag{6}$$

The employer separation probability $p_t^S = p_t^{EN} + p_t^{EE}$ satisfies $p_t^S = 1 - \exp(-h^S)$. Substitute in this definition and the first term by $e_{t+1}^{<1}$, rearrange, and obtain:

$$\exp(-h_t^{EN} - h_t^{EE}) = \frac{e_{t+1} - e_{t+1}^{<1}}{e_t}. \tag{7}$$

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

Given the value of h_t^{EN} pinned down by Equation (2) and the observables e_t, e_{t+1} and $e_{t+1}^{<1}$, Equation (7) can be solved for a unique value of h_t^{EE}.

2.2 Transitions between unemployment and employment

I also measure transition rates from unemployment to employment (h^{UE}) and from employment to unemployment (h^{EU}) following the approach developed by Shimer (2012) and that relies on stocks of unemployed and unemployed for less than one month.[6] Different from Shimer (2012), for the US, and Elsby et al. (2013), for European countries, my measure of the stock of unemployed for less than one month comprises only individuals who moved from employment to unemployment within the past month. This finer measurement of the stock of unemployed (made possible by the availability of nonemployment duration data in the EULFS and longitudinal data in the CPS) implies that my transition measures are conceptually equivalent to those obtained using longitudinal observations of individual labor market states.[7]

2.3 Implementation

To measure monthly transition rates, I combine the framework developed in Subsection 2.1 with EULFS data at a weekly frequency. I face three challenges. First, I want to implement a consistent definition of a spell duration of less than one month across different months. Second, there are observations with missing answers to the questions necessary to compute spell durations. Third, the EULFS is designed to produce representative estimates at a quarterly frequency. I state each problem in detail and how I address it in Appendix A.1.

2.4 Validation

The cross-sectional approach used in this paper recovers the probability that the average individual in state i leaves to state j at least once during that month. In other words, it recovers the same probability as longitudinal approaches that compute it by dividing the ratio of the flow of workers from state i to j (obtained by longitudinally linking individual observations of labor market states) across the month by the stock of individuals in state i in the previous month. Therefore, given the assumptions of my accounting framework, my transition estimates are equivalent to

[6] *Mutatis mutandis*, this entails the same steps as those I described in Subsection 2.1 to measure the transitions rates between employment and nonemployment.

[7] Shimer (2012) and Elsby et al. (2013) measure unemployment-outflow and inflow rates, since their estimates comprise flows between unemployment and employment/nonparticipation.

longitudinal estimates based on monthly data. To validate my approach, I compare my estimates to available estimates based on the longitudinal approach.[8] In the following paragraphs, I summarize the conclusions of those comparisons. Due their size, the supporting exhibits and calculations are presented in Section OA.4.

The main challenge when comparing my estimates to longitudinal ones is the lack of monthly estimates for European countries. As emphasized in the literature (see e.g. Gomes (2015) and references therein), time aggregation implies that transition rates measured at different frequencies have different levels and volatilities, although the effect on their cyclicality seems to be less pronounced (see e.g. Elsby et al. (2009)). With the exception of the UK, I could not access longitudinal monthly estimates. The first validation exercise compares my estimates with those produced by Postel-Vinay and Sepahsalari (2023) for the UK that relies on data from a different survey (the British Household Panel Survey/Understanding Society). The comparison strongly validates my approach. The two time series of the EE probability have similar levels, trends and cyclical profiles (see Figure OA.2).

In a second validation exercise I compare the quarter averages of my monthly estimates to quarterly longitudinal estimates for Portugal and the UK measured using the national versions of the EULFS. To overcome the differences in levels and volatilities between transition estimates measured at different frequencies induced by time aggregation, I follow Postel-Vinay and Sepahsalari (2023) and normalize the longitudinal quarterly estimates so that they have the same mean and standard deviation as my cross-sectional monthly estimates. The behavior of the two sets of estimates is very similar (see Figure OA.3).

In my last validation exercise I compare quarter averages of my monthly estimates to quarterly longitudinal estimates made available by Eurostat since 2010 for almost all countries. Eurostat does not publish quarterly time series of the aggregate EE transition rate, so I compare transitions between nonemployment (unemployment) and employment. As in previous comparisons, I normalize the longitudinal time series to render them comparable to my cross-sectional estimates. The main conclusion of this exercise is that, up to 2020, the time series variation is fairly similar across the two sets of estimates for most countries. However, from 2021 onwards, for some countries there is a substantial discrepancy between the dynamics of the series. My analysis suggests that discrepancy originates in the redesign of the EULFS adopted in 2021 (see chapter 3 of Eurostat (2024)). Specifically, the rates of

[8] In practice, due to biases plaguing the two approaches (attrition bias, recalled error bias, etc.), some differences are to be expected. Identifying and quantifying those biases is beyond the scope of this paper. Ahn and Hamilton (2021) pursue that endeavor in the context of measuring transitions between unemployment and employment with CPS data.

missing answers to measure employer and nonemployment spell durations increased substantially from 2021 for some countries. This is likely a temporary effect due to the adoption of new measurement concepts and procedures, but that is difficult to diagnose/address without further data. I discuss this issue and present additional analysis in Section OA.4.3.

2.5 Other estimates of EE mobility in Europe

In the Introduction I mentioned that, compared to existing papers measuring EE transition rates for European countries, mine is the only one that produces quarterly time series of monthly transition rates for a fairly long period, covering all quarters of the calendar year and a large set of countries, and using data that is easily accessible by researchers and that will continue to be produced in the future. I now substantiate that statement. Jolivet et al. (2006) measure (average) monthly transition rates over the period from 1994 to 1997 for 10 European countries using data from the European Community Household Panel (ECHP). Engbom (2021) measures yearly transitions at a yearly frequency for prime-age men using data from the ECHP and the European Union Statistics on Income and Living Conditions (EU-SILC) for 12 European countries over two decades from the mid 1990s to the mid 2010s. Hence, the data in those papers lack either the long-time horizon or the high-frequency dimension afforded by my estimates. Donovan et al. (2023a) relies mostly on EULFS longitudinal data, and measure quarterly transitions for 26 out of the 31 countries covered by the EULFS over the period from the mid 2000s to 2020.[9] However, since EULFS longitudinal identifiers are scrambled across years, for 21 of the 26 countries they cannot estimate transitions for all quarters of the calendar year. Moreover, their estimates based on EULFS data are based on a version of the microdata that ends in 2020.[10] For the remaining five countries in their sample they use microdata from the national labor force surveys that require a specific application process to access/purchase, and whose documentation is often only available in the original language. Section OA.1 describes in more detail my empirical approach and those of Jolivet et al. (2006), Engbom (2021) and Donovan et al. (2023a).

[9] The time period covered in their sample varies substantially by country. For example, for the Netherlands it is one year, whereas it is over 20 years for the UK. As I describe in more detail in Section 3, in my analysis I only considered the 20 largest economies out of the 31 countries covered in the EULFS. Among the 20 largest economies, my sample and Donovan et al. (2023a)'s do not exactly overlap. My sample covers Germany, Belgium, Finland and Norway, but not Greece, the Netherlands, Romania and Switzerland, and vice versa for Donovan et al. (2023a)'s sample.

[10] The new version of the EULFS microdata does not include any longitudinal identifiers.

3 Data

This section describes the data used to estimate transition rates in European countries. Appendix A.2 describes the remaining data used in the paper.

The EULFS is a harmonized labor force survey comprising the majority of European countries. 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 Eurostat processes the data produced by member-countries and distributes the harmonized microdata to the public.[11] Even though most countries' labor force surveys include a longitudinal dimension with a rotational structure, the EULFS is available to researchers as time series of cross sections.[12] The EULFS microdata is composed of yearly and quarterly extracts. The yearly extracts go further back in time, but suffered several changes, 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 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 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.[13]

In the reference week civilian individuals are classified as either employed or nonemployed according to the International Labor Organization 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 individuals are classified as nonemployed. The unemployed are nonemployed individuals who actively searched for work in the past four weeks and who are available to start working. The EULFS asks all nonemployed individuals if they had any previous work experience and, to those who respond affirmatively, asks the year and month in which they last worked. Similarly, all employed individuals are asked the year

[11] I use the January 2024 release of the Scientific Use Files (see link), which covers all available periods up to December 2022 for almost all countries.

[12] '*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.*' Eurostat (2021) (p. 68).

[13] For some countries and years, the survey is run only in one week in each month. This data structure can be accommodated within my measurement framework, so I include those time periods as well.

and month in which they started working continuously for their current employer or as self-employed. I use that information to calculate the duration of nonemployment spells (in months) of nonemployed individuals, and the duration of spells with the current employer (tenure) of all employed workers.

The EULFS microdata quarterly extracts include information on 31 countries. I selected the 20 largest economies measured by GDP in 2023. From my initial sample, I removed Greece, the Netherlands, Romania and Switzerland.[14] For the remaining countries, I excluded certain periods at the beginning of the sample when I judge the extent of missing answers to the questions necessary to estimate individual nonemployment and/or employer spell durations to be too great. Table 1 provides, for each sampled country, the average monthly sample size, the time period covered in my analysis, and the EULFS acronym used in the paper. The countries are ordered by the size of their economy in 2023. From the first quarter of 2021 the EULFS suffered a major redesign (see chapter 3 of Eurostat (2021)). As I document in Section 2.4, for some countries, the extent of missing answers to the questions necessary to measure employer and nonemployment spell durations increased dramatically. Therefore, I excluded observations from 2021 onwards. In my analysis the working-age sample comprises individuals between 20 and 64 years old.

4 EE mobility in Europe and the US

This section presents the main patterns of variation in my estimates of transition rates. I first document average cross-country differences in EE mobility and in its size relative to separations from employment. Second, I describe time variation in the EE probability within each country, focusing on cyclical variation and comovement with the other transition rates.

[14]In the Netherlands the question eliciting nonemployment duration refers exclusively to jobs with duration greater than one year, which does not allow one to estimate the transition rate from nonemployment to employment. For Greece the estimates of the transition rates from nonemployment/unemployment to employment are systematically negative during the Great Recession's trough. For Romania the estimates of the employer-to-employer transition rate are systematically negative, which is not plausible. For Switzerland the estimates of the transition rates from nonemployment/unemployment to employment are not robust. I analyzed the available documentation for the various countries, but could not find information allowing me to detect the potential sources of the problems.

Table 1: Description of the sample

Country name	Country acronym	Star month	End month	Sample size
Germany	DE	2005m1	2019m12	23,423
France	FR	2014m1	2020m12	21,356
United Kingdom	UK	1999m3	2020m9	18,956
Italy	IT	2004m1	2020m12	27,908
Spain	ES	1999m1	2020m12	33,417
Poland	PL	2000m1	2020m12	17,672
Belgium	BE	1999m1	2020m12	5,247
Sweden	SE	2006m10	2020m12	15,878
Austria	AT	2005m7	2020m12	8,940
Czechia	CZ	2002m1	2020m12	10,741
Ireland	IE	2010m1	2020m12	10,053
Portugal	PT	1998m1	2020m12	8,165
Norway	NO	2011m1	2020m12	4,989
Denmark	DK	2001m1	2020m12	5,286
Hungary	HU	1999m1	2020m12	12,512
Finland	FI	2003m1	2020m12	6,553

Notes: EULFS data. The column 'Sample size' reports the average number of observations per month in 2014 with valid cross-sectional weight, labor force status, and of the working age (between 20 and 64 years old). The sample for Germany does not cover the year 2020.

4.1 Cross-country variation in steady-state transitions

In my steady-state analysis, I focus on the period from 2014 to 2019, in between the Great Recession's prolonged aftermath and the start of the Pandemic recession. Besides the exclusion of the recessionary periods, the main reason to choose this period is to include as many countries as possible, namely France.[15] Even though I focus on this narrower period, as will become clear in Section 4.2, differences in the levels of countries' transition rates are persistent throughout the sample period, so the main conclusions of the analysis in this section hold more broadly.

Figure 1 reports average turnover probabilities for all the sampled countries, where countries are grouped according to their geography/institutions as indicated in the legend.[16] The top plot of Figure 1 displays the transition from nonemployment to employment (p^{NE}) on the vertical axis and the employer separation probability ($p^{EE} + p^{EN}$) on the horizontal axis. These two quantities summarize

[15]The EULFS quarterly extracts for France start in 2003:q1, but there is a significant break in the short-tenure stock around 2014, and the implied employer separation rate (h^s) before 2014 seems implausibly high. Although I cannot detect a change in the text of the questions eliciting this information, the French Labor Force Survey suffered a major overhaul in 2013 with the stated goal of aligning its concepts and measurements with the EULFS guidelines.

[16]I report transition probabilities rather than transition rates to facilitate comparisons with estimates reported in the literature.

the extent of aggregate labor turnover. Visual inspection of the top plot reveals very large cross-country variation in both probabilities, and a very tight positive association between them. The country with the highest levels of labor turnover is the US, whereas Eastern European countries display the lowest levels. Among the remaining countries, Spain and three Nordic countries (Denmark, Finland and Sweden) are more or less in the midpoint of the two extremes, whereas the other countries are closer to the Eastern European cluster.

The bottom plot of Figure 1 displays the employer-to-employer transition probability (p^{EE}) on the vertical axis and the transition from employment to nonemployment (p^{EN}) on the horizontal axis. Similar to the top plot, there are large differences in the levels of both probabilities across countries, as well as a positive association between them. Focusing first on variation along the vertical axis, the average EE probability differs markedly across countries, ranging from 0.3 percent (Italy) to 2.8 percent (Sweden), with a large fraction of countries displaying rates around 1 percent. As in the top plot, the countries that exhibit the highest levels of employer-to-employer turnover are three Nordic countries and the US, and those with the lowest levels are Eastern European (now accompanied by Spain, and even surpassed by Italy). Despite the positive association between the size of p^{EE} and p^{EN}, it is visible to the naked eye that a few countries stand out by having lower values of the transition ratio p^{EE}/p^{EN}, namely Italy and Spain and, to a lesser degree, Austria, Finland and the US (numbers are reported in the fourth column of Table 2). The transition ratio measures the size of employed workers' transitions to another employer vs to nonemployment (I refer to it as *relative EE mobility*). The values for the US are about half the size of those of many European countries (e.g. Germany, France, the UK, Sweden and Denmark). This constitutes a very large transatlantic difference in the composition of employer separations. In Section 5.2 I will provide an economic interpretation of this observation.

Up to now, I have described EE mobility together with mobility between nonemployment and employment. While that is justified by the large size of flows between nonparticipation and employment, the unemployed are more closely attached to the labor market and allow for a more direct comparison of turnover into and out of employment across countries.[17] Table 2 reports sample averages of the EE transition probability and of nonemployment and unemployment transition probabilities. The bottom row displays cross-country sample averages. As expected, the transition to

[17]The degree of labor market attachment of nonparticipating workers is likely to differ more across countries, whereas the concept of unemployment (and its measurement) is quite consistent across countries. I thank one anonymous referee for making this point and for arguing for the importance of analyzing transitions between unemployment and employment in the paper.

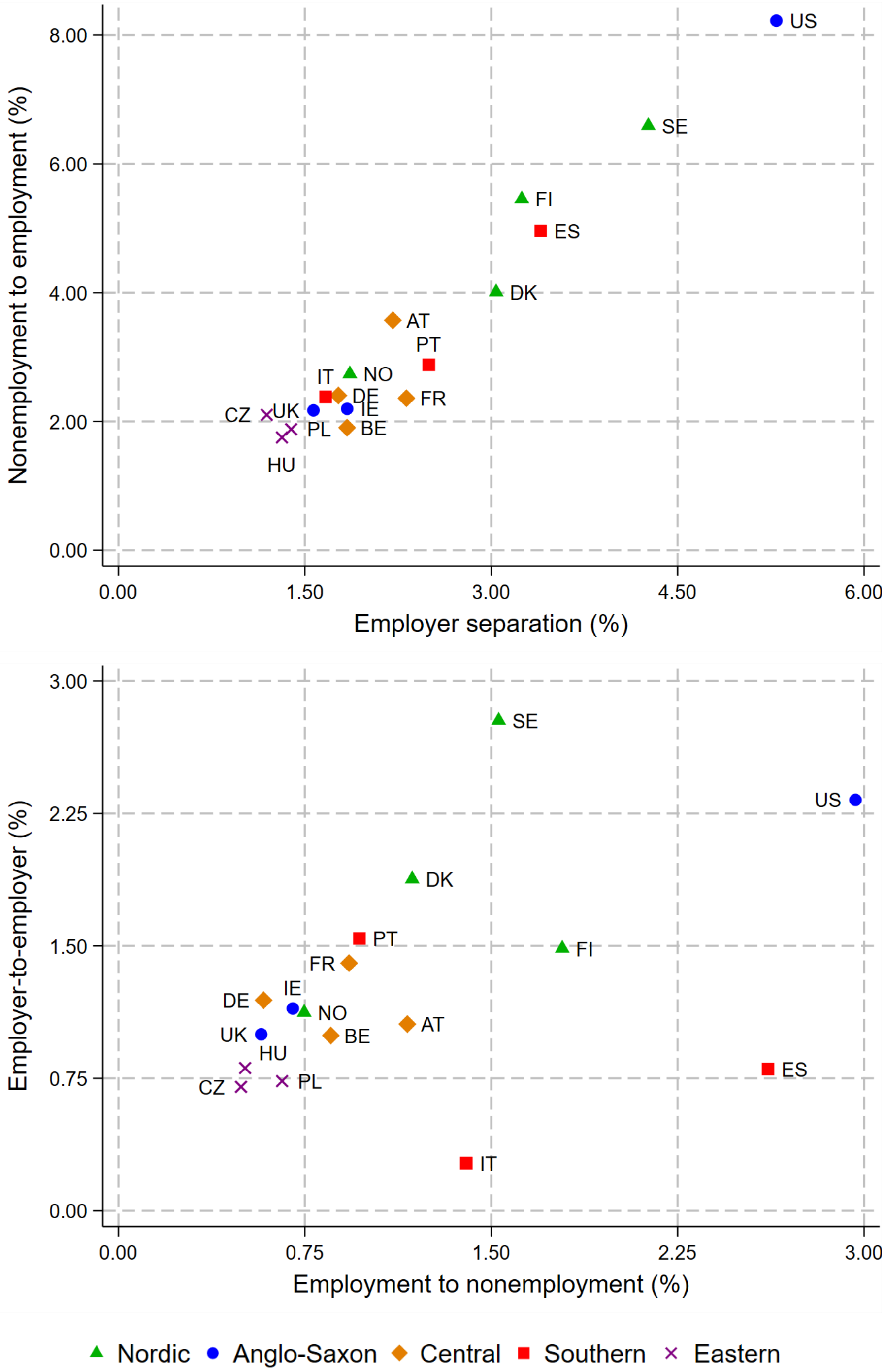

Figure 1: Average transition probabilities in European countries and the US

Notes: Top plot: p^{NE} on y-axis and $p^{S} = p^{EN} + p^{EE}$ on x-axis. Bottom plot: p^{EE} on y-axis and p^{EN} on x-axis. Coverage: Working-age sample, 2014 – 2019. Author's calculations based on data from the EULFS, the CPS and Fujita et al. (2024).

employment is much larger among the unemployed compared to the nonemployed. The average ratio p^{UE}/p^{NE} is 2.5 and there is substantial variation across countries. The value of p^{UE} for the US stands out by its very large size (25%), but in relative terms (p^{UE}/p^{NE} is equal to three for the US) it is just as large, or larger, for other countries (the UK, Poland, Czechia and Hungary). By definition, the separation rate of employed workers is higher to nonemployment than to unemployment. The average ratio p^{EN}/p^{EU} is equal to 2.2, but it varies less across countries. Czechia and the US are again the countries with the largest ratios. Despite the patterns just described, cross-country variation in relative EE mobility based on the separation rate to unemployment is similar to the one based on the separation rate to nonemployment (cf. fourth and seventh columns of Table 2). Italy and Spain remain the two countries with lowest relative EE mobility, followed by the US, Finland and Austria, and some European countries have much higher relative EE mobility compared to the US (e.g. Germany, Sweden, the UK and Denmark).

4.2 Time-series variation in transition rates

In my time-series analysis I restrict the sample to countries with data covering the Great and the Pandemic recessions and their preceding expansions. Figure 2 displays time series of transition rates across employers (p^{EE}), from employment to nonemployment (p^{EN}), and from unemployment to employment (p^{UE}), along with the unemployment rate, and the recession dates when available.[18,19] Because of the stronger job attachment of the unemployed, the transition probability from unemployment to employment closely tracks time variation in job creation and, therefore, it is more useful than p^{NE} to benchmark the cyclicality of p^{EE}. Since classification of newly nonemployed workers between unemployment and nonparticipation can be fuzzy (viz. newly nonemployed workers may be initially classified as nonparticipants even though they remain attached to the labor market), p^{EN} is a more comprehensive measure, and likely a better tracker of the dynamics of job destruction. Inspection of the time series of p^{EN} and p^{EU} seems to confirm this: although the two series comove very closely, in a few countries p^{EN} appears more countercyclical (see Figure OA.7).

Inspection of the plots pertaining to European countries highlights that time variation in countries' EE probabilities (solid lines) is substantial. With the naked

[18] I use the country-specific business-cycle dates proposed by the Economic Cycle Research Institute and the NBER's Business Cycle Dating Committee for the US. For Eurozone countries not covered by the ECRI, I use the dates proposed by the Euro Area Business Cycle Network.

[19] Figure 2 reports $p^{UE}/10$ to facilitate comparisons with the other transition probabilities.

Table 2: Transition probabilities in European countries and the US

		Nonemployment			Unemployment		
	p^{EE}	p^{NE}	p^{EN}	p^{EE}/p^{EN}	p^{UE}	p^{EU}	p^{EE}/p^{EU}
United States	2.3	8.2	3.0	0.8	24.7	1.2	2.0
Germany	1.2	2.4	0.6	2.0	6.6	0.3	4.5
France	1.4	2.4	0.9	1.5	5.2	0.5	2.8
United Kingdom	1.0	2.2	0.6	1.7	6.7	0.3	3.6
Italy	0.3	2.4	1.4	0.2	4.6	0.6	0.5
Spain	0.8	5.0	2.6	0.3	8.7	1.8	0.4
Poland	0.7	1.9	0.7	1.1	7.2	0.3	2.3
Belgium	1.0	1.9	0.9	1.2	5.1	0.4	2.5
Sweden	2.8	6.6	1.5	1.8	10.4	0.7	3.8
Austria	1.1	3.6	1.2	0.9	7.5	0.4	2.4
Czechia	0.7	2.1	0.5	1.4	6.3	0.2	3.9
Ireland	1.1	2.2	0.7	1.6	5.9	0.4	2.9
Portugal	1.5	2.9	1.0	1.6	6.0	0.6	2.6
Norway	1.1	2.7	0.7	1.5	7.3	0.3	3.5
Denmark	1.9	4.0	1.2	1.6	9.3	0.6	3.4
Hungary	0.8	1.8	0.5	1.6	5.8	0.2	3.4
Finland	1.5	5.5	1.8	0.8	8.8	0.7	2.0
Sample average	1.3	3.4	1.2	1.3	8.0	0.6	2.7

Notes: Average transition probabilities expressed in percent from 2014 to 2019. The bottom row reports cross-country averages. Author's calculations based on data from the EULFS, Fujita et al. (2024), and the CPS. Coverage: Working-age sample.

eye, one can see large variation around recessions, as well as low-frequency variation in the time series of some countries. In my description I will focus on the behavior of the EE probability around recessions and its comovement with the unemployment rate. However, due to the presence of secular trends in either p^{EE} and/or the unemployment rate in some countries, this is difficult to discern visually. Therefore, to complement the visual analysis I report the correlation coefficients between the cyclical components of the unemployment rate and p^{EE} obtained by removing a very low-frequency trend, as advocated by Shimer (2012) (see in the first column of Table 3).

The information displayed in Figure 2 reveals large procyclical variation in the EE probability around recessions in the majority of countries. Moreover, the correlation coefficients between the cyclical components of p^{EE} and the unemployment rate (displayed in the first column of Table 3) are large and negative for all countries except Czechia and Hungary (where they are zero) and Portugal and Sweden (where they are negative but small). In most countries, the solid lines drop around the time of the cyclical ramp-up in the unemployment rate, recover as the unemployment rate declines, and grow steadily during expansions. The procyclicality of the EE probability is more clearly evident in countries that experienced several, rather moderate, cycles in the unemployment rate throughout the sample period (Austria, Belgium and Finland). Another 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. A second group of countries experienced either large and/or very persistent rises in unemployment during the Great Recession (Denmark, Italy, Spain, and the UK). Consistent with a procyclical behavior of the EE probability, in those countries one observes sharp and/or long-lasting falls in p^{EE} during the Great Recession. In all four countries, the recovery in the EE probability in the Great Recession's aftermath is quite sluggish, although this observation is confounded by secular declines in EE mobility.

Given the variety of labor markets covered in the sample, there are naturally some exceptions to the procyclical pattern described in the previous paragraph. In Czechia and Hungary, from the early 2000s onwards, the EE probability fluctuates at a high frequency around a stable mean, but displays no comovement with the unemployment rate except during the Pandemic Recession. However, during the Great Recession, the directions of change in p^{EN} (dashed line) and p^{UE} (long-dashed line) are consistent with the conventional view: the jump in the unemployment rate is accompanied by a spike in employment destruction and reduction in job creation. In contrast, the EE probability does not exhibit noticeable variation during that time window. A third exception is given by Portugal during the Great Recession. Due to a strong upward trend in EE mobility starting in 2006, it is difficult to discern with the naked eye the extent of cyclical variation around the Great Recession. However, on impact the drop in EE is very small compared to the extraordinary rise in unemployment. On the other hand, during the Covid-19 recession the fall in the EE probability is extraordinary. Last, 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.

To characterize the cyclical comovement between p^{EE}, p^{UE} and p^{EN}, I combine the information displayed in Figure 2 with correlation coefficients between the cyclical components of the time series displayed in Table 3. One would expect a tight positive comovement between p^{UE} and p^{EE}. If the pools of employed and unem-

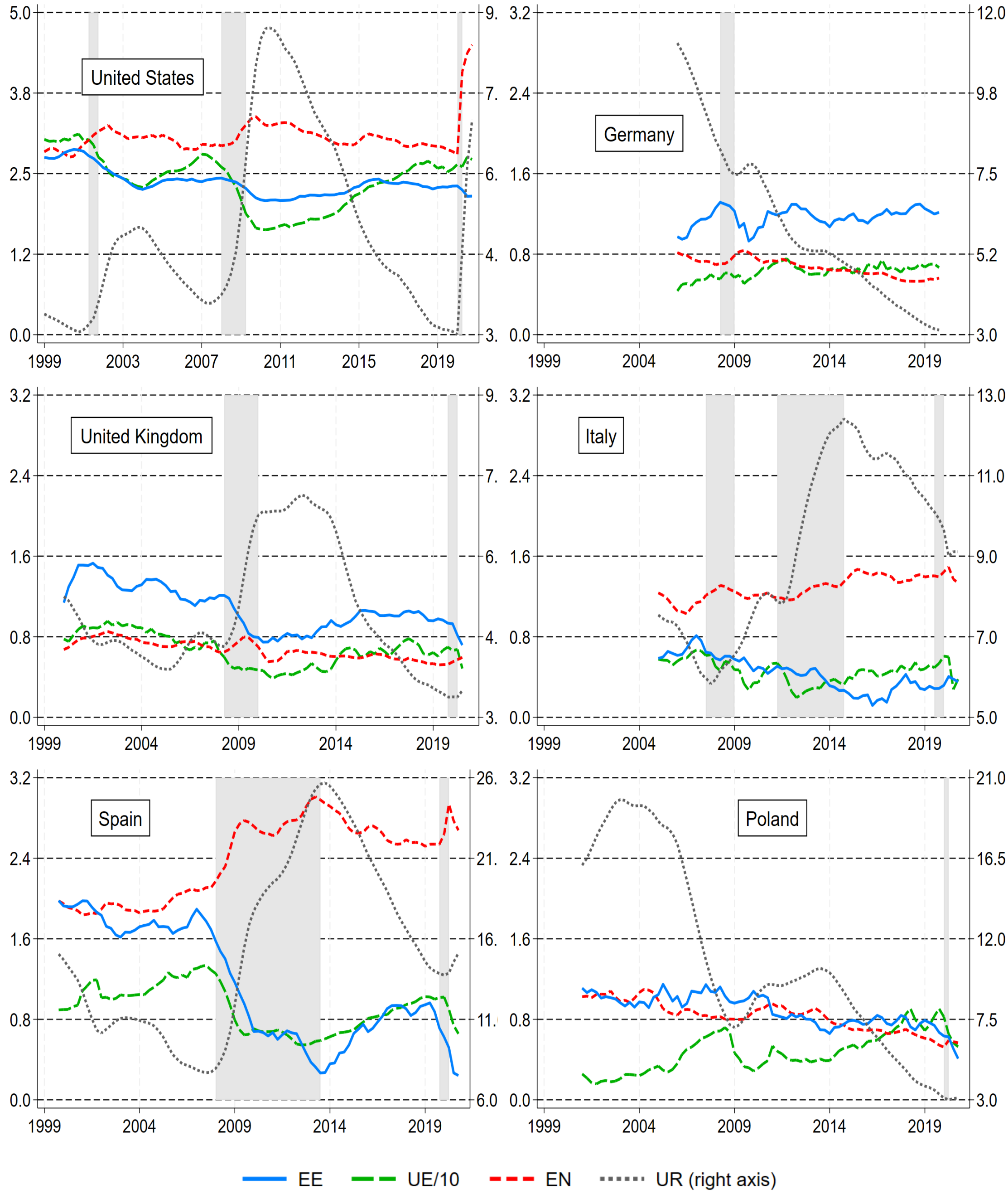

Figure 2: Time series of transition probabilities

Notes: All series are quarter averages of monthly time series smoothed by a 12-month trailing moving average, and expressed in percent. Coverage: Working-age sample from 1999:1 to 2020:4 (start and end dates differ across countries). Author's calculations based on data from the EULFS, Fujita et al. (2024) and the CPS.

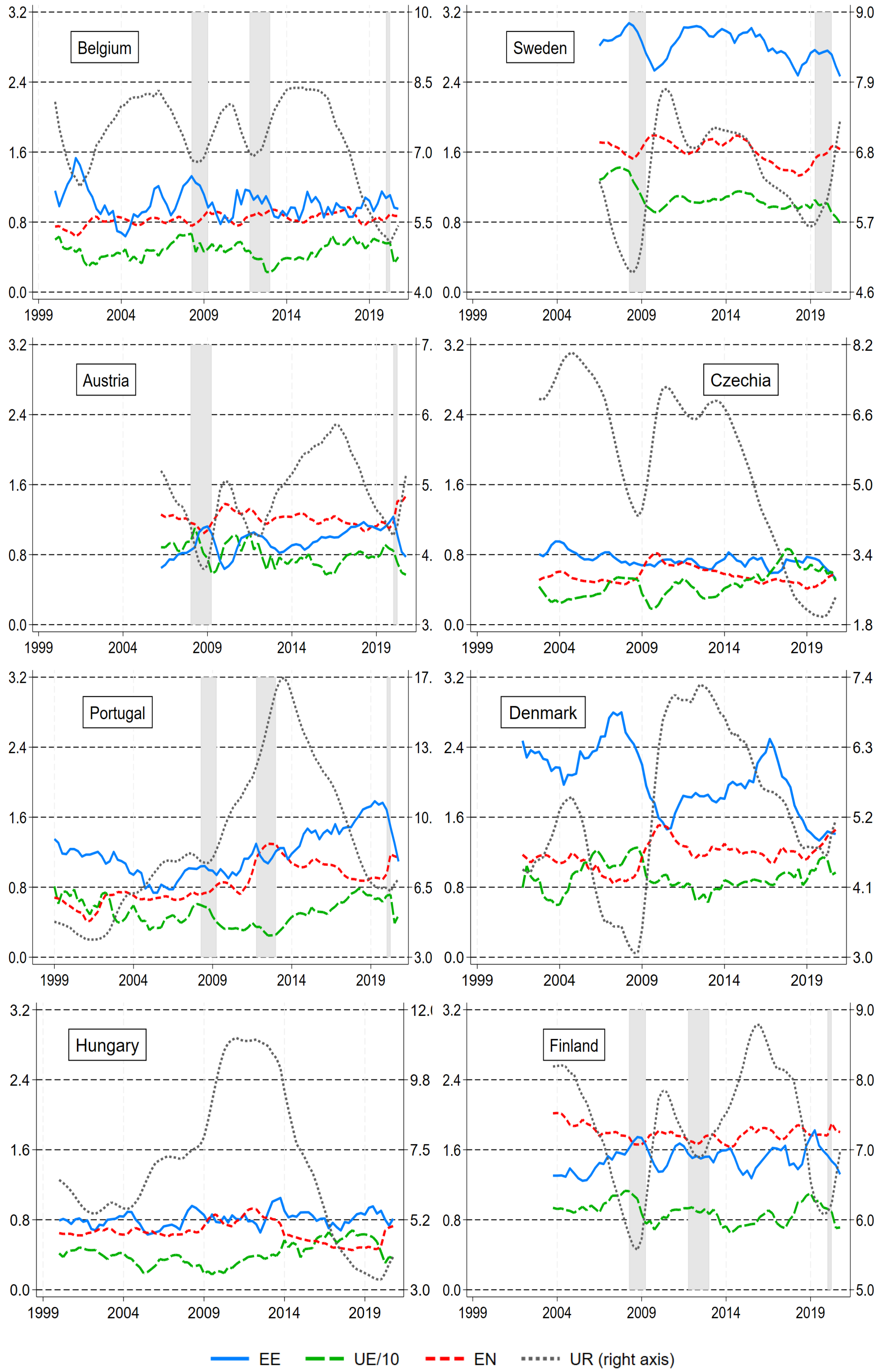

Figure 2 (Cont.): Time series of transition probabilities

Table 3: Cyclicality and comovement of the EE probability

		Nonemployment		Unemployment	
	(p^{EE}, ur)	(p^{EE}, p^{NE})	(p^{EE}, p^{EN})	(p^{EE}, p^{UE})	(p^{EE}, p^{EU})
United States	-0.79	0.22	-0.49	0.76	-0.57
Germany	-0.75	-0.05	-0.36	0.41	-0.49
United Kingdom	-0.75	0.66	0.11	0.81	-0.37
Italy	-0.54	-0.45	-0.53	-0.10	-0.64
Spain	-0.68	0.68	-0.70	0.74	-0.60
Poland	-0.37	0.21	-0.26	0.44	-0.21
Belgium	-0.45	-0.54	-0.46	0.10	-0.42
Sweden	-0.24	0.69	0.23	0.63	0.22
Austria	-0.57	-0.44	-0.70	0.15	-0.77
Czechia	-0.02	-0.25	-0.25	0.15	-0.17
Portugal	-0.15	0.38	0.06	0.50	0.07
Denmark	-0.46	-0.48	-0.75	0.24	-0.65
Hungary	0.05	-0.23	0.03	0.05	0.01
Finland	-0.60	0.07	-0.63	0.31	-0.67

Notes: The table reports contemporaneous correlation coefficients between time series of quarter averages of the monthly series smoothed by a 12-month trailing moving average and detrended by an HP filter with smoothing parameter equal to 10^5. ur denotes the unemployment rate. Author's calculations based on data from the EULFS, Fujita et al. (2024) and the CPS, 1998:1 – 2020:4 (start and end dates differ across countries), working-age sample.

ployed workers compete for the same vacancies and have similar search behavior and matching efficiency, and if employers cannot direct their job-posting efforts to either pool of searchers, the two series should be driven by the same force (job creation) and, hence, display a strong positive and contemporaneous comovement. The numbers reported in the second column of Table 3 offer a mixed assessment of this prediction. While in many countries the coefficients are positive and sizable (US, Germany, UK, Spain, Poland, Sweden and Portugal), in the remaining countries the correlations are either small, zero or negative. On the other hand, as is clearly visible in Figure 2, the employment-separation probability is countercyclical in most countries. Since job creation is procyclical and job destruction countercyclical, one would expect p^{EE} and p^{EN} to comove negatively at business-cycle frequencies. Inspection of Table 3 confirms this prediction. All countries bar the UK, Sweden, Portugal and Hungary, display negative contemporaneous correlation coefficients between p^{EE} and p^{EN}. For completion, Table 3 also reports the correlations coefficients between the cyclical components of p^{EE}, p^{NE} and p^{EU}. As expected, the comovement between p^{NE} and p^{EE} is weaker than that between p^{UE} and p^{EE}, and the comovement between p^{EE} and each separation probability (p^{EN}

and p^{EU}) is very similar (if anything it is slightly stronger with p^{EU}).

4.3 Summary and relation to existing evidence

In my analysis of average turnover rates across countries I documented substantial variation in transition rates across countries and highlighted two main patterns. First, consistent with the earlier literature on unemployment turnover (e.g. Elsby et al. (2013)), I find that transition rates are much higher in the US compared to the average European country, as well as substantial variation among European countries. In particular, some Nordic countries and Spain have higher turnover rates compared to other European countries. Second, while I find considerable variation in EE mobility across countries, its patterns are distinct from those observed for nonemployment/unemployment turnover. Specifically, I show that cross-country variation in relative EE mobility (or the composition of employer separations) is considerably lower in Finland, the US, Italy and Spain compared to many other European countries.

The first finding is consistent with other estimates reported in the literature (Jolivet et al. (2006), Engbom (2021) and Donovan et al. (2023a)), even though some of the specific cross-country patterns differ across the various papers. However, that comparison is not necessarily informative, since those estimates of EE mobility are based on different samples, frequency, time period, concepts and measurements. Concerning the second finding, Jolivet et al. (2006) report the fraction of job spells ending with a job-to-job transition which is related to my measure of relative EE mobility. Using their metric, they also find that Italy and Spain exhibit the lowest levels, about a third of the values of Denmark, France and Great Britain. Different from my results, they report that the US has values only about 5 to 10 percentage points lower than those of the three European countries. As I explain in detail in Section OA.1, Jolivet et al. (2006)'s estimates of EE mobility differ from mine in many significant respects. Therefore, that comparison is not necessarily informative. In contrast, in Figure OA.6 I replicate the bottom plot of Figure 1 using the estimates produced by Donovan et al. (2023a), which can be made more comparable to mine, and find a similar pattern. In conclusion, while my first finding is consistent with the conventional wisdom, my second finding paints a novel picture of transatlantic differences in labor market behavior.

In my time-series analysis of the EE probability, I document that differences in EE mobility across countries are persistent. When I focus on cyclical variation, I first find that the EE probability is procyclical in most European countries. Second, I document substantial heterogeneity in the strength of the positive comovement between the EE probability and the transition probability from unemployment to employment. For some countries (most notably the US, the UK, Spain and Sweden) it is quite strong, but it is weaker or absent in the other countries. Third, I document a very consistent pattern of negative cyclical comovement between the EE probability and the separation probabilities from employment.

The common observation in my sample of countries of procyclical EE mobility is consistent with the analysis of monthly time series based on labor force survey data for a single country (Postel-Vinay and Sepahsalari (2023) for the UK, Nakamura et al. (2020) for Canada, and Fujita et al. (2024) for the US).[20] Nakamura et al. (2020) and Fujita et al. (2024) document a very tight positive comovement between the transition rate from unemployment to employment and the EE transition rate in Canada and the US. My analysis comprising several European countries suggests those patterns may be specific to some countries (viz. Anglo-Saxon).

5 Insights from the job-ladder framework

Job-ladder models offer a theoretical framework to interpret variation in employer-to-employer mobility and its relationship to wage variation. The first models in this tradition (see Burdett (1978) and Burdett and Mortensen (1998)), as well as a large subsequent literature (see Hornstein et al. (2011) and references therein), aimed at explaining cross-sectional wage dispersion. A common feature in these models is the role of employer-to-employer mobility as a source of labor market power. Over the past decade a new vintage of models have extended the job-ladder framework to understand its implications for aggregate labor market dynamics (see Moscarini and Postel-Vinay (2018)'s survey). Moscarini and Postel-Vinay (2023) and Faccini and Melosi (2023) incorporate the job-ladder framework in a monetary New Keynesian business-cycle model. Both models deliver a structural equation linking the dynamics of wage inflation to different indicators of EE mobility.

In this section I use arguably the simplest version of the job-ladder model (viz. Burdett (1978)) to provide an economic interpretation of the variation in turnover rates documented in the previous section, and to assess the empirical relevance of EE mobility to understand fluctuations in nominal wage growth in European countries and the US.[21,22] Specifically, I focus on turnover rates affecting employed workers

[20] Donovan et al. (2023b)'s analysis of the average response of EE mobility using quarterly variation suggests a more muted response. However, their sample covers a very different set of countries, many of which are not in Europe and are developing economies.

[21] I use Burdett (1978)'s model since the limitations of the EULFS data (lack of longitudinal identifiers and individual wages) make it difficult to plausibly inform richer models with data.

[22] The behavior of employers is not modeled in Burdett (1978)'s model, but one can think of it

(the transition rate across employers and the separation rate from employment). In the job-ladder model all nonemployed individuals are unemployed. However, as in my descriptive analysis, I prefer to use the separation rate from employment to nonemployment in my baseline calibration of the job-ladder model. Section OA.8 presents the same results as those reported in Subsections 5.2, 5.3 and 5.4 below using the transition rate from employment to unemployment, and shows that they are very similar.

5.1 The job-ladder model

The model is populated by ex ante equal, infinitely-lived and risk-neutral individuals who are either employed or unemployed. Time is continuous, and individuals sample job offers sequentially at Poisson rates λ^u and λ^e, respectively when unemployed and employed. Each job offer is characterized by a (fixed) wage which is an iid draw from a nondegenerate wage-offer distribution $F(w)$. The lowest wage offered in the economy is set at the level of the reservation wage w^*, under the assumption that no employer would post an offer that would never be accepted. Jobs are destroyed at rate σ.

In this environment, individuals maximize the present-discounted value of their future utility by choosing a reservation wage w^*, such that all job offers below w^* are rejected and job offers paying w^* or above are accepted when workers are unemployed. The reservation wage is given by the expression below:

$$w^* = b + (\lambda^u - \lambda^e) \int_{w^*}^{w^{\max}} \frac{1 - F(z)}{r + \sigma + \lambda^e[1 - F(z)]} dz, \tag{8}$$

where b is the flow value of unemployment and r is the discount rate. The second optimal individual decision is, when employed, to accept any wage offer paying strictly above the current wage.

Given the wage-offer distribution $F(w)$, let $G(w)$ denoted the steady-state wage distribution function among employed workers ($\bar{G}(\cdot)$ and $\bar{F}(\cdot)$ denote the respective survivor functions), and u the unemployment rate. For any wage level w, assume that, in steady state, flows in and out of $G(w)$ balance. That is, that a mass $(1-u)G(w)[\sigma + \lambda^e \bar{F}(w)]$ of employed workers flowing out exactly equals the mass $u\lambda^u F(w)$ of unemployed workers flowing into $G(w)$. Since $F(w^*) = 0$, these flow balance restriction imply that $u\lambda^u = (1-u)\sigma$. Combined, these flow-balance re-

as a model of monopsonistic competition, where employers face an upward-sloping labor supply curve on their own wage, given the wages paid by other employers. The higher the competition between employers, the closer workers' wages are to the value of their marginal product.

strictions imply the following expression for the steady-state cross-sectional wage distribution:

$$G(w) = \frac{\sigma F(w)}{\sigma + \lambda^e \bar{F}(w)}. \tag{9}$$

Let $\kappa^e \equiv \lambda^e/\sigma$ be the index of job-ladder reallocation. It measures the average number of job offers received during an employment spell of average duration. Rearranging Equation (9), delivers the following equation:

$$\kappa^e = \frac{F(w) - G(w)}{G(w)[1 - F(w)]} \tag{10}$$

Note that, when κ^e is positive, the distribution of accepted wages $G(.)$ 1st-order stochastically dominates the wage-offer distribution $F(.)$. Furthermore, the larger κ^e, the greater the gap between the two distributions, and the closer is the average wage to the maximum wage. In other words, κ^e measures workers' ability to earn higher wages (labor market power).[23]

In this economy the average employer-to-employer transition rate h^{EE} is:

$$h^{EE} = \int_{w^*}^{w^{\max}} \lambda^e \bar{F}(w) dG(w) \tag{11}$$

Using integration by parts and Equation (9) implies the equation below

$$h^{EE} = \frac{\sigma(\lambda^e + \sigma)\ln(1 + \lambda^e/\sigma)}{\lambda^e} - \sigma, \tag{12}$$

which shows that the extent of EE mobility (h^{EE}) depends positively on the job-destruction rate σ and the job-offer arrival rate of the employed λ^e.

5.2 Cross-country steady-state variation

A key implication of the job-ladder model described above is that observed aggregate EE mobility depends positively on two distinct sources: the job-offer arrival rate to employed workers and the job-destruction rate. On the one hand, an increase in the number of job offers to the employed implies that more workers accept to change employer. Importantly, those EE moves constitute movements up the job ladder (upward mobility), since workers only accept to change employer if the wage offer dominates their current wage. On the other hand, a higher job-destruction rate means that, in steady state, more workers occupy the lower rungs of the job ladder, where upward EE mobility is more frequent (since a higher proportion of wage

[23] κ^e plays a similar role in wage-posting models in the vein of Burdett and Mortensen (1998).

offers are accepted by the employed). Then, to interpret cross-country differences in EE mobility based on the job-ladder model one must account for the relative importance of those two sources of variation, which is what I do next.

Taking the transition rate from employment to nonemployment (h^{NE}) as the empirical counterpart of the job-destruction rate (σ), one can combine it with an estimate of the hazard rate to change employers (h^{EE}) and Equation (12) to back out an estimate of the job-offer arrival rate to the employed. Table 4 reports the calibrated parameters of the job-ladder model for each country. Scanning the first two columns shows that there is a clear association between the calibrated values of λ^e and the values of p^{EE} (reported in the first column of Table 2), but also some differences. Specifically, countries with comparatively low relative EE mobility (Austria, Finland, Italy, Spain and the US) have relatively fewer opportunities for upward mobility (λ^e) conditional on their values of p^{EE}. The implied values for the ratio $\kappa^e \equiv \lambda^e/\sigma$ are displayed in the third column of Table 4. Cross-country variation in κ^e is substantial and its patterns mirror those of relative EE mobility displayed in Table 2. There are very large differences across countries. Germany, Sweden and the UK have much higher values than countries like Italy, Spain, the US, Finland and Austria. According to the job-ladder model, the ability of US workers to climb up the job ladder is very low compared to some of its European counterparts, and this is chiefly because they are far more likely to fall off the job ladder due to the elevated frequency of job-separation shocks.

In Section OA.6 I calibrate the job-ladder model to compute a measure of frictional wage dispersion, namely the Mean-min ratio popularized by Hornstein et al. (2011)). In addition to data on nonemployment transition rates, I use information on countries' unemployment income replacement rates. As is well known, the degree of income insurance in the US is low compared to most European countries. All else equal, that would imply higher frictional wage dispersion in the US vs Europe. On the contrary, my quantitative exercise highlights that cross-country differences in income insurance are second order compared to differences in κ^e. Indeed, compared to the US, the Mean-min ratio is similar or higher in many European countries.

5.3 Time variation in the employed job-offer arrival rate

Equation (12) establishes a positive relationship between the EE transition rate and the job-destruction rate (σ), whose empirical counterpart is the transition from employment to nonemployment. Figure 2 highlights large and persistent countercyclical fluctuations in p^{EN} in some European countries. If employment separations lead the transmission of the business-cycle to the labor market, according to the model,

Table 4: Job-ladder model calibrated parameters

	λ^e	σ	κ^e
United States	0.08	0.030	2.6
Germany	0.10	0.006	16.8
France	0.08	0.009	8.5
United Kingdom	0.07	0.006	11.6
Italy	0.01	0.014	0.4
Spain	0.02	0.026	0.8
Poland	0.03	0.007	4.9
Belgium	0.05	0.009	5.3
Sweden	0.20	0.015	12.8
Austria	0.04	0.012	3.4
Czechia	0.04	0.005	7.6
Ireland	0.07	0.007	10.4
Portugal	0.09	0.010	9.6
Norway	0.06	0.008	8.4
Denmark	0.11	0.012	9.5
Hungary	0.05	0.005	9.5
Finland	0.05	0.018	2.9
Sample average	0.07	0.012	7.4

Notes: The displayed parameters are calibrated by the average transition rates from 2014 to 2019. The bottom row reports cross-country averages. Author's calculations based on data from the EULFS, Fujita et al. (2024), and the CPS. Coverage: Working-age sample.

the EE rate should respond with a lag to increases in p^{EN}. To assess the importance of that effect on the comovement of transition rates, I combine Equation (12) and my transition rate estimates to recover a time series of the job-offer arrival of the employed (λ^e) for each country.[24] Table 5 reports correlation coefficients between the cyclical components of λ^e, the unemployment rate, and the transition rates from unemployment to employment and from employment to nonemployment. The patterns of comovement of λ^e are much more consistent across countries compared to those of p^{EE}. Specifically, λ^e is negatively correlated with the unemployment rate and p^{NE} in all countries, and positively correlated with p^{UE} in all countries except Italy. This suggests that the structure of the job-ladder model is useful to isolate time variation in EE mobility that reflects workers' opportunities to climb up the job ladder.

[24]Using wage data, Jolivet (2009) finds support for the steady-state assumption (viz. Equation (12)) in US CPS monthly data.

Table 5: Cyclicality and comovement of job-offer arrival rate of employed

	(λ^e, ur)	(λ^e, p^{UE})	(λ^e, p^{EN})
United States	-0.84	0.71	-0.73
Germany	-0.63	0.25	-0.63
United Kingdom	-0.72	0.76	-0.16
Italy	-0.49	-0.16	-0.63
Spain	-0.69	0.71	-0.79
Poland	-0.42	0.46	-0.52
Belgium	-0.43	0.10	-0.60
Sweden	-0.34	0.17	-0.65
Austria	-0.54	0.15	-0.79
Czechia	-0.24	0.43	-0.70
Portugal	-0.37	0.50	-0.47
Denmark	-0.60	0.34	-0.89
Hungary	-0.34	0.35	-0.53
Finland	-0.57	0.20	-0.77

Notes: The reported contemporaneous correlation coefficients use quarter averages of the monthly series detrended by an HP filter with smoothing parameter equal to 10^5. ur denotes the unemployment rate. Author's calculations based on EULFS, Fujita et al. (2024), and CPS data from 1998:1 – 2020:4 (starting and end dates differ across countries), working-age sample.

5.4 Job-ladder reallocation and wage inflation

In the job-ladder model described in Section 5.1, the wage-offer distribution is fixed, so the model is silent about how changes in labor productivity affect the job-offer and job-destruction arrival rates and, by extension, the wage-offer distribution. Moscarini and Postel-Vinay (2016) have analyzed those effects in the heterogeneous-firm version of Burdett and Mortensen (1998)'s model, where firm's productivity includes an aggregate component. Specifically, they offer a comparative-statics result establishing that productivity shocks affect the wage-offer distribution through various effects, including a competition effect. The competition effect captures the response of labor demand (by varying the arrival rates of job separations and job offers) to a shock to labor productivity, and the subsequent effect on the equilibrium posted wage in every active firm. According to that result, an increase in labor productivity that raises the job-ladder reallocation index leads to an increase the wage-offer distribution.[25] This powerful insight implies that the competition

[25] In their comparative-statics result (Equation (4)), Moscarini and Postel-Vinay (2016) focus on the response of the job-offer arrival rate of the employed to an increase in the aggregate component of firms' productivity. It is straightforward to show that the same result holds for the job-ladder reallocation index (i.e. λ_1/δ, in their notation) when the job-destruction rate

effect raises the wages of both employer-movers (a higher job-ladder reallocation index implies that workers climb the job-ladder faster) and employer-stayers (a higher job-ladder reallocation index implies that the wage-offer distribution shifts upwards).

As a preliminary assessment of the hypothesis that shocks to labor productivity are transmitted to wages via the job-ladder reallocation index, Figure 3 reports time series of the job-ladder reallocation index and wage inflation for the US and the 13 European countries in my sample.[26] Focusing first on the wage inflation series (dashed line), there are no visible trends in any country.[27] Second, turning to the job-ladder reallocation index (solid line), it exhibits a very striking procyclical pattern in the majority of European countries, and that follows quite closely the wage-inflation time series. Table OA.2 substantiates this visual reading by reporting correlation coefficients between wage inflation and lags of the job-ladder reallocation index. In almost all countries (the exceptions are Austria, Finland and Hungary) the correlation coefficients are positive and sizable.

To quantify the dynamic relation between wage inflation and the job-ladder reallocation index, and to gauge the potential relevance of the job-ladder reallocation index to predict wage inflation, I estimate empirical wage Phillips curves by OLS. Specifically, for each country, I run two sets of regressions. First, I regress wage inflation on the job-ladder reallocation index (or its lags), and display the coefficients in the even-numbered columns of Table 6. Second, I regress wage inflation on the job-ladder reallocation index (or its lags) and lagged price inflation (to account for inflation expectations), and report the coefficients in the odd-numbered columns of Table 6.[28] In all countries except Austria, Hungary, Finland and Spain, the job-ladder reallocation index coefficient is positive, large and strongly statistically significant.

is allowed to respond to productivity shocks. The worker block of that model is akin to the Burdett (1978).

[26] Appendix A.2.2 provides details on the data sources used to construct the wage and price inflation measures used in my analysis.

[27] First, I exclude data from 2020, since in many European countries there is an extraordinarily upward jump due to the Pandemic recession. That jump is consistent with employees being paid a monthly salary and working very few hours, as was the case in the wage-subsidy programs put in place in most European countries. Second, the lack of trend variation in both series leads me to focus exclusively on variation in the raw series, i.e. without detrending.

[28] All variables used in the OLS regressions are previously standardized, so that the regression coefficients are comparable across alternative specifications.

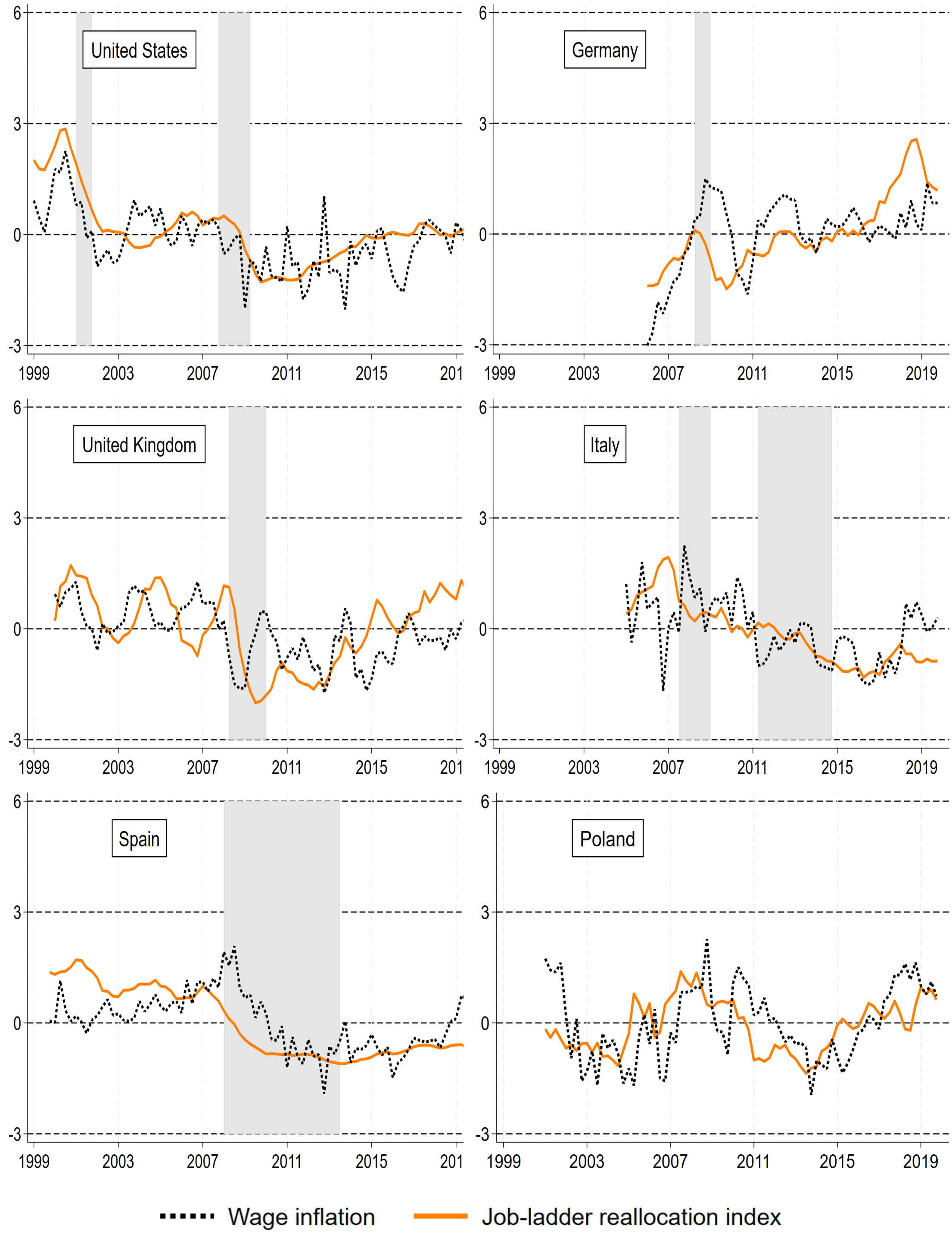

Figure 3: Wage inflation and the job-ladder reallocation index

Notes: Dotted line: quarterly wage inflation smoothed by a four-quarter trailing moving average. Solid line: job-ladder reallocation index ($\kappa^e = \lambda^e/\sigma$). The job-ladder reallocation index is computed as the quarter average of the monthly series smoothed by a 12-month trailing moving average. Both series are normalized for comparability. Author's calculations based on data from the EULFS, the CPS, Fujita et al. (2024), Eurostat's Quarterly National Accounts and the US Bureau of Labor Statistics.

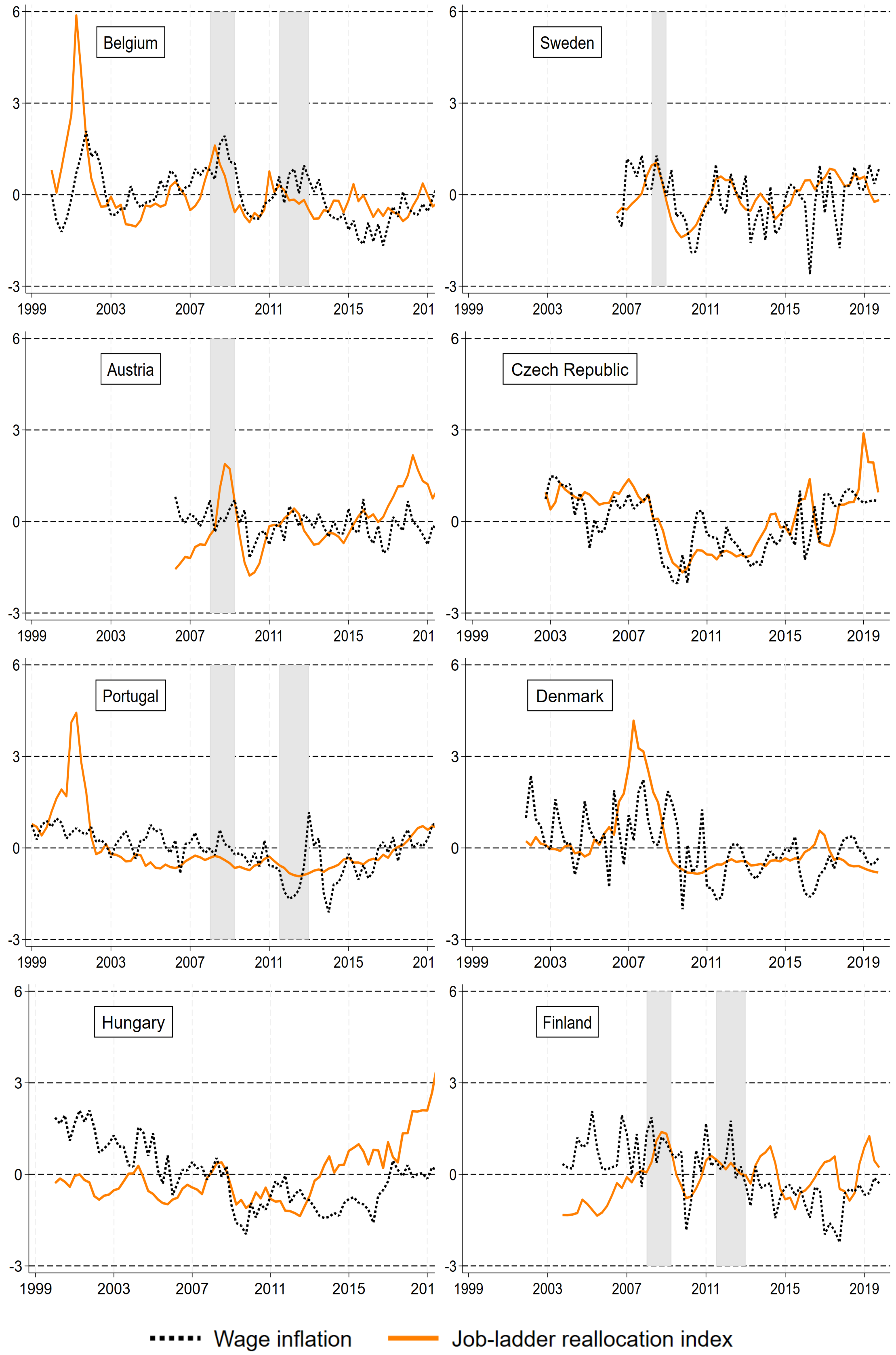

Figure 3 (Cont.): Wage inflation and job-ladder reallocation index

Table 6: Empirical wage Phillips curve slope parameter

	L0		L1		L2	
	(1)	(2)	(3)	(4)	(5)	(6)
United States	0.62	0.60	0.58	0.56	0.54	0.52
	0.00	0.00	0.00	0.00	0.00	0.00
Germany	0.42	0.18	0.43	0.27	0.44	0.35
	0.11	0.22	0.05	0.11	0.02	0.05
United Kingdom	0.27	0.25	0.19	0.18	0.14	0.11
	0.02	0.03	0.12	0.17	0.30	0.42
Italy	0.47	0.41	0.49	0.46	0.57	0.57
	0.02	0.15	0.01	0.12	0.00	0.03
Spain	0.47	-0.05	0.50	0.08	0.53	0.29
	0.00	0.80	0.00	0.74	0.00	0.38
Poland	0.56	0.54	0.80	0.79	0.86	0.84
	0.00	0.00	0.00	0.00	0.00	0.00
Belgium	0.27	0.23	0.38	0.34	0.46	0.43
	0.01	0.01	0.00	0.00	0.00	0.00
Sweden	0.51	0.38	0.47	0.29	0.48	0.27
	0.01	0.08	0.05	0.27	0.04	0.25
Austria	0.03	0.07	0.07	0.08	0.06	0.05
	0.73	0.29	0.45	0.35	0.54	0.49
Czech Republic	0.60	0.69	0.57	0.69	0.50	0.62
	0.00	0.00	0.00	0.00	0.00	0.00
Portugal	0.32	0.20	0.31	0.18	0.30	0.16
	0.00	0.02	0.00	0.03	0.00	0.06
Denmark	0.36	0.28	0.42	0.34	0.47	0.40
	0.00	0.00	0.00	0.00	0.00	0.00
Hungary	0.01	0.00	0.04	0.01	0.03	0.01
	0.97	1.00	0.78	0.91	0.84	0.89
Finland	-0.03	-0.33	-0.16	-0.49	-0.17	-0.40
	0.92	0.27	0.54	0.05	0.49	0.12

Notes: The table reports, for each country, the coefficients of the job-ladder reallocation index, and its lags, from a wage inflation OLS regression (top row), and respective p-values calculated using Newey-West autocorrelation robust covariance for eight lags (bottom row). The even (odd) numbered columns refer to OLS regressions including a constant (a constant and lagged price inflation). The job-ladder reallocation index series are calculated by the author using data from the EULFS, Fujita et al. (2024) and the CPS, and are quarter averages of the monthly series filtered by a 12-month trailing moving-average. The wage inflation time series are taken from the US Bureau of Labor Statistics and Eurostat, and are expressed as first-differences of the logged seasonally-adjusted compensation per hour index measured at quarterly frequency, and subsequently smoothed by a four-quarter trailing moving average.

5.5 Summary and relation to existing evidence

I use my data to estimate and analyze cross-country and time-series variation in the job-ladder reallocation index. First, I found substantial cross-country variation in that indicator, and that the US has a much lower level compared to the average European country. This finding suggests that labor market power is higher in the average European country compared to the US. Ridder and Van den Berg (2003) and Jolivet et al. (2006) estimate similar indicators for a smaller set of countries covering a few years of data in the 1990s. In addition to sample differences, their results are not directly comparable to mine. Jolivet et al. (2006) also observe wage data, which allows them to estimate a finer measure of the job-reallocation index that distinguishes EE mobility involving a wage cut.[29] Ridder and Van den Berg (2003) estimate the same indicator as I do (they label it *index of search frictions*), but they measure it using unemployment duration data. Second, I show that, according to the job-ladder model, the acyclical behavior of EE mobility in some countries can be attributed to the countercyclicality of the employment-separation probability. When I account for that effect, the resulting time series of the job-offer arrival rate of the employed displays a more consistent procyclical behavior across countries compared to the raw EE probability. Jolivet (2009) analyzes the cyclical patterns of his structural estimates of the job-offer arrival rate of the employed and of the probability that dismissed workers immediately receive an outside offer (what he labels *job-reallocation shocks*) on a decade of US CPS data (1996 to 2006). He finds that the incidence of job-reallocation shocks is more strongly procyclical than the job-offer arrival rate of the employed. Again, in addition to sample differences, his results are not directly comparable to mine, since his model includes job-reallocation shocks and the two transition parameters are identified both by transitions and wage data.

Motivated by recent work on the cyclical job-ladder (see Moscarini and Postel-Vinay (2018) and references therein), I have established that the job-ladder reallocation index is strongly procyclical and closely tracks the dynamics of aggregate wage inflation (also when controlling for lagged price inflation) in the US and most European countries. My results add to earlier work documenting a positive empirical relationship between measures of EE mobility and wage dynamics and/or wage or price inflation in the US (e.g. Moscarini and Postel-Vinay (2016), Karahan et al. (2017), Faberman et al. (2020)).

6 Conclusion

The first goal of this paper was to provide estimates of the aggregate EE transition rate for European countries. I developed a novel approach to measure the EE transition rate, implemented it in EULFS data, and obtained plausible estimates for a large set of European countries. The raw data that I used can be easily accessed by researchers, and I expect others to scrutinize and improve my current

[29]Using my notation, Jolivet et al. (2006) indicator is defined as follows $\kappa_e = \frac{\lambda_e}{\sigma+\lambda_r}$, where λ_r is a job-reallocation shock, or a Godfather shock, a wage offer that cannot be refused.

estimates. More importantly, I also hope others will want to use my estimates to answer distinct research questions.

The second goal of the paper was to use the job-ladder framework to draw economic insights from cross-country and time-series variation in EE mobility. My analysis delivered novel empirical results. First, I showed that the US exhibits low relative EE mobility compared to many European countries which, according to the job-ladder model, implies that US workers have lower labor market power compared to their European peers. This fact could offer a novel ingredient to understand cross-country differences in labor market performance, which so far have mostly focused on differences in nonemployment/unemployment turnover. Second, I showed that the ratio of the job-offer and job-destruction arrival rates of the employed is strongly procyclical, and displays a strong comovement with wage inflation in most countries. This result is not only useful to track the dynamics of aggregate wages, but it also constitutes a useful guide to modeling approaches that aim to understand the dynamics of wage inflation based on the job-ladder framework.

The key evidence for the US that motivates Moscarini and Postel-Vinay (2023)'s New-Keynesian business-cycle model with on-the-job search is 1) the strong countercyclicality of the acceptance ratio (the ratio of the EE transition rate and the transition from unemployment to employment) and 2), the strong negative correlation between the acceptance ratio and wage inflation. My paper proposes an alternative measure of the role of EE mobility in the transmission of labor demand shocks based on the static version of Burdett and Mortensen (1998), and shows that it has strong empirical support.[30] Since my goal was to show that the patterns in the data that I produced are well aligned with the implications of a very well-established theory of labor market equilibrium, I pursued a very simple approach. Moscarini and Postel-Vinay (2023) show that their model delivers a structural wage Phillips curve that depends on the unemployment rate and the acceptance ratio. Using a cross-sectional design similar to Hazell et al. (2022) and US state-level data they show that the acceptance ratio is a more important predictor of wage inflation compared to the unemployment rate. Exploring similar approaches in my sample of European countries, and contrasting the predictive power of the job-ladder reallocation index against the acceptance ratio and the unemployment rate, are important endeavors for future research.

[30]In an earlier version of the paper I showed that, for the European countries in my sample, the job-ladder reallocation index performs better than the acceptance ratio. This is because, for some European countries, the acceptance ratio is not negatively correlated with wage inflation. Those results are available on request.

Appendix

A.1 Measurement of transition rates

This section states the three problems that I face in implementing my measurement framework on EULFS data and how I address each of them.

A.1.1 Definition of spells with duration less than one month

In the EULFS spell durations are measured in months. Consider the definition of a spell with duration (strictly) less than one month. For each individual I observe the survey reference week (the calendar week to which her labor market situation refers), the spell reference month (the calendar month in which the spell started) and a quarterly cross-sectional weight (produced by Eurostat and included in the EULFS microdata). The stock of individuals in spells with duration less than one month only counts individuals whose spell start date (the calendar month) is the same as the survey reference month (the calendar month of the reference week) and weighs them using the individual survey design weights.[31] This approach is clearly problematic. Since calendar months have different lengths (measured by the number of weeks), the stock of individuals in short duration spells is affected by the length of the month. To address this problem, I apply the definition used in the CPS to measure the duration of search spells, which is *less than five weeks*, to European countries' data. However, since I do not observe spell durations in weeks, I need to determine how to best approximate the stock of workers in spells of duration less than five weeks using spell durations measured in months.

To illustrate my solution, consider the measurement of the stock of individuals in a nonemployment spell of duration less than five weeks in each week of a given month ($n^{<5\mathrm{w}}$). Since all months have five weeks or less, all individuals with spell duration equal to zero months (their stock is denoted $n^{=0}$) are counted in $n^{<5\mathrm{w}}$. Regarding individuals with duration equal to one month (their stock is denoted $n^{=1}$), it is unclear. Some will likely have durations longer than five weeks. For example, an individual who becomes nonemployed in the first week of a month comprised of five weeks and is surveyed in the last week of the following month. This example suggests that nonemployment duration depends on two observable variables: the survey reference week and the number of weeks in the month the spell started. Individuals who are interviewed in weeks closer to the end of the calendar month, i.e. those whose *week number in the month* (wim) is high, are

[31]For those individuals the spell duration is equal to zero months.

more likely to have longer spell durations. Individuals who started a spell in a month with more weeks (for individuals in $n^{=1}$ this is always the previous month, so I denote the number of weeks in the month the spell started as #wpm) are more likely to have a longer spell duration. Knowledge of wim and #wpm, however, is not enough to solve the indeterminacy caused by the fact that the calendar week in which individuals start their spell is unobserved. To solve it, I assume that the distribution of the spells' starting week in the previous month is uniform. This assumption implies a weight function of $n^{=1}$ given wim and #wpm, and a specific formula to calculate $n^{<5\text{w}}$ for any calendar week:[32]

$$n^{<5\text{w}}(\text{wim}, \#\text{wpm}) = n^{=0} + \sum_{\text{wim}=1}^{4} \left(n^{=1} \times (5 - \text{wim})/\#\text{wpm}\right). \tag{13}$$

I apply the same formula to calculate the short tenure stock in each week of any month. Because my approach relies on an assumption, in Section OA.2 I discuss the implications of an alternative assumption. Specifically, I show that assuming that 1) employment spells end at the last week of the month, and 2) employer spells start at the first week of the month, implies results that are not plausible.

A.1.2 The missing duration problem

To apply the formula described in Equation (13), I first need to calculate the stocks of individuals with duration equal to zero and one month (for the nonemployed that is $n^{=0}$ and $n^{=1}$) for every calendar week. This is trivial to obtain were if not for the fact that some individuals' spell duration is missing. To solve this problem, I only need to classify the nonemployed and employed with missing durations as having a duration lower or equal than one (zero) month(s).[33]

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. In my analytical framework (see Subsection 2.1, $n_{t+1}^{<1}$ measures newly nonemployed individuals, that is, individuals who were employed at time t and have become nonemployed during time $t+1$. Therefore, I

[32]There is a typo in Equation (13) in an older version of the paper, namely Borowczyk-Martins (2022). I thank Mike Major for pointing it out, and for suggesting the current (more elegant) statement of the formula.

[33]In other words, for the nonemployed, I need to estimate $n^{\leq 0}$ and $n^{\leq 1}$, since $n^{\leq 0} = n^{=0}$ and $n^{\leq 1} - n^{\leq 0} = n^{=1}$.

can classify all individuals with no previous employment experience as having spell duration greater than one month. For the remaining individuals, in general, it is not possible to determine the length of their nonemployment spell. Regarding the employed, there are only two sources of missing duration: either the month or the year of the start date of the current employer spell is missing.

Section OA.3 shows time series of the share of observations in each month that, due to missing answers to the survey questions mentioned above, cannot be classified as having a spell duration lower or equal than zero/one month. For the majority of countries and time periods, those shares are very small, both among the employed and the nonemployed.[34] Therefore, to address this missing-data problem, I make a missing-completely-at-random assumption, which implies assuming that missing durations are independent of the true, unobserved durations. Under this assumption, the number of nonemployed (employed with their current employer) with duration equal to zero (one) is equal to the product of the fraction of nonemployed (employed) with duration equal to zero (one) month among those with non-missing durations and the count of nonemployed (employed) in the reference week.

A.1.3 Monthly transitions at quarterly frequency

As shown above, it is straightforward to calculate transitions at a monthly frequency. One simply sums the weekly stocks for the respective calendar month (for the nonemployed I sum $n^{<5w}$ across all weeks comprised in the month). However, because the frequency of the EULFS is quarterly, transition estimates at a monthly frequency are noisy and, due to the sample design, not necessarily representative of the population in the month. My approach to deal with this problem is twofold. First, I apply a 12-month trailing moving-average filter to the raw monthly series. In addition to removing noise, this approach is useful to remove seasonal variation.[35] Second, I average the monthly transition rates for each quarter. Hence, although

[34] As I discuss in more detail in Subsection 2.4, the redesign of the EULFS implemented in 2021 increased the incidence of missing answers dramatically for many countries, which led me to exclude post-redesign observations from my analysis.

[35] There are more sophisticated approaches to deal with seasonality. A common approach is to implement the X13-ARIMA algorithm developed by the US Bureau of Labor Statistics. For the US, when filtering nonseasonally adjusted data using the 12-month trailing moving-average filter produces time series of transition probabilities that are nearly identical to the BLS X13 seasonally adjusted series, with the exception of the Pandemic recession period. When I seasonally adjust the series of European countries 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 pre-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 that approach is not feasible when applied to five time series in each of the 13 countries in my sample.

I measure monthly time series of transition rates, all the results displayed and analyzed in the paper are based on quarter averages of those monthly series. This additional aggregation step is necessary to satisfy Eurostat's reliability thresholds.[36]

I considered two alternative approaches to deal with noisy estimates at a monthly frequency. The first one entails computing monthly transition rates at a quarterly frequency, following Elsby et al. (2013)'s imputation method. That approach produces quarterly time series of monthly transition rates that, when adjusted by a trailing four-quarter moving-average, are virtually identical to the quarter averages of my filtered monthly estimates. The second alternative, also proposed by Elsby et al. (2013), consists of using information on worker stocks in spells of duration longer than one month to measure monthly transition rates. As argued in their paper, that 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 transition rates based on stocks of employed/nonemployed at longer durations. Therefore, I prefer to estimate average transition rates using only the transition rates based on stocks of duration less than five weeks, since they are the least affected by potential duration dependence and, therefore, are more directly comparable to US estimates.[37]

A.2 Additional data

A.2.1 US transition rates data

To measure transitions rates between employment and nonemployment/unemployment, I use the CPS Basic Monthly files provided by IPUMS (Integrated Public Use Microdata Series) Flood et al. (2022). Specifically, I link individual observations on

[36] Eurostat's EULFS reliability thresholds are defined in terms of the weighted count of individuals in each calendar quarter and country. To determine whether my measurements satisfy the reliability thresholds I take e.g. the stock of nonemployed for less than one month in each calendar quarter and country and compare it to the respective threshold.

[37] The problem of duration dependence is distinct from time aggregation. My estimates of h^{NE} and h^{S}, and by extension of h^{EE}, are not immune to time-aggregation bias, because in reality individuals can change labor market states and employer within the month, and that will not be adequately counted in the monthly stocks of individuals in spells with duration less than five weeks. Mukoyama (2014) shows how to correct for time-aggregation bias in p^{EE}. However, the direction and size of his adjustment depend on the probability that a nonemployed worker is recalled by her previous employer. Unfortunately, that quantity is not possible to estimate with EULFS data, and I am not aware of any estimates for European countries. In any case, using US data Mukoyama (2014) concludes that his time-aggregation correction changes the measured EE probability by a small magnitude and leaves its cyclicality largely unchanged. Since the employment-separation and the EE rates in European countries are smaller compared to the US, the effect of the time-aggregation correction is likely to be even smaller.

labor market state across two consecutive months to measure gross flows between employment and nonemployment and between employment and unemployment.[38] My estimate of the EE transition probability was retrieved from the Federal Reserve Bank of Philadelphia's webpage and is the most recent version (at the time of writing) of the adjusted series produced by Fujita et al. (2024), which accounts for selection bias due to changes in the CPS Respondent Interview Policy.

A.2.2 Data on price and wage inflation

For European countries I measure wage and price inflation using data from the Quarterly National Accounts made available by Eurostat.[39] Specifically, I measure wage inflation by the ratio of Compensation of Employees, at current prices, in units of national currency, by Hours worked, using a domestic definition of employee, in thousands of hours worked. Both measures comprise all NACE activities. My measure of price inflation uses the GDP implicit price deflator index, with base year 2005, using price data expressed in national currency at market prices. All variables used in my calculations are seasonally and calendar adjusted by Eurostat. I obtained comparable measures for the US from FRED.[40] The measure of wage inflation is based on series COMPNFB, Hourly Compensation for All Employed Persons in the Nonfarm Business Sector, Index 2012=100, Quarterly, Seasonally Adjusted. My measure of price inflation is based on series IPDNBS, Implicit Price Deflator for All Employed Persons, Index 2012=100, Quarterly, Seasonally Adjusted.

References

Ahn, Hie Joo and James D Hamilton, "Measuring labor-force participation and the incidence and duration of unemployment," *Review of Economic Dynamics*, 2021.

Bertola, Giuseppe and Richard Rogerson, "Institutions and labor reallocation," *European economic review*, 1997, *41* (6), 1147–1171.

Blanchard, Olivier and Pedro Portugal, "What hides behind an unemployment rate: Comparing Portuguese and US labor markets," *American Economic Review*, 2001, *91* (1), 187–207.

[38]I use longitudinal weights to obtain population counts.

[39]I retrived the data from the following webpage https://ec.europa.eu/eurostat/web/main/data/database.

[40]From the following webpage https://fred.stlouisfed.org/release?et=&ob=t&od=&pageID=4&rid=47&t=&tg=&tt=.

Borowczyk-Martins, Daniel, "Employer-to-employer Transitions in Europe," *working paper*, March 2022.

— **and David Pacini**, "Measuring Labor Market Transitions in Europe: Identification and Validation Analysis," *working paper*, January 2022.

— **and** — , "Measuring labor market transitions with time series of cross sections," *Economics Letters*, 2024, *237*, 111650.

Burdett, Ken, Carlos Carrillo-Tudela, and Melvyn Coles, "Wage inequality: A structural decomposition," *Review of Economic Dynamics*, 2016, *19*, 20–37.

Burdett, Kenneth, "A theory of employee job search and quit rates," *The American Economic Review*, 1978, *68* (1), 212–220.

— **and Dale T Mortensen**, "Wage differentials, employer size, and unemployment," *International Economic Review*, 1998, pp. 257–273.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman, "Labor market dynamics and development," *The Quarterly Journal of Economics*, 2023, *138* (4), 2287–2325.

— **,** — **, Joseph H Pedkte, and Todd Schoellman**, "Labor Market Anatomy of a Macroeconomic Crisis," *working paper*, 2023.

Elsby, Michael W L, Ryan Michaels, and Gary Solon, "The ins and outs of cyclical unemployment," *American Economic Journal: Macroeconomics*, 2009, *1* (1), 84–110.

Elsby, Michael WL, Bart Hobijn, and Ayşegül Şahin, "Unemployment dynamics in the OECD," *Review of Economics and Statistics*, 2013, *95* (2), 530–548.

Engbom, Niklas, "Labor Market Fluidity and Human Capital Accumulation," *mimeo*, December 2021.

Eurostat, "EU Labour Force Survey Database User Guide," November 2021. https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS-Database-UserGuide.pdf.

— , "EU Labour Force Survey Database User Guide," February 2024. https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS_Database_UserGuide_2021.pdf.

Faberman, R Jason, Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa, "The shadow margins of labor market slack," *Journal of Money, Credit and Banking*, 2020, *52* (S2), 355–391.

Faccini, Renato and Leonardo Melosi, "Job-to-Job Mobility and Inflation," *FRB of Chicago Working Paper*, 2023.

Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren, *Current Population Survey: Version 10.0 [dataset]* Integrated Public Use Microdata Series 2022.

Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay, "Measuring Employer-to-Employer Reallocation," *American Economic Journal: Macroeconomics*, 2024, *16* (3), 1–51.

Gomes, Pedro, "The importance of frequency in estimating labour market transition rates," *IZA Journal of Labor Economics*, 2015, *4*, 1–10.

Hairault, Jean-Olivier, Thomas Le Barbanchon, and Thepthida Sopraseuth, "The cyclicality of the separation and job finding rates in France," *European Economic Review*, 2015, *76*, 60–84.

Hazell, Jonathon, Juan Herreno, Emi Nakamura, and Jón Steinsson, "The slope of the Phillips Curve: evidence from US states," *The Quarterly Journal of Economics*, 2022, *137* (3), 1299–1344.

Hornstein, Andreas, Per Krusell, and Giovanni L Violante, "Frictional wage dispersion in search models: A quantitative assessment," *American Economic Review*, 2011, *101* (7), 2873–98.

Jolivet, Grégory, "A longitudinal analysis of search frictions and matching in the US labor market," *Labour Economics*, 2009, *16* (2), 121–134.

Jolivet, Gregory, Fabien Postel-Vinay, and Jean-Marc Robin, "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US," *European Economic Review*, 2006, *50* (4), 877–907.

Karahan, Fatih, Ryan Michaels, Benjamin Pugsley, Ayşegül Şahin, and Rachel Schuh, "Do job-to-job transitions drive wage fluctuations over the business cycle?," *American Economic Review*, 2017, *107* (5), 353–57.

Ljungqvist, Lars and Thomas J Sargent, "Two questions about European unemployment," *Econometrica*, 2008, *76* (1), 1–29.

Mortensen, Dale, *Wage dispersion: why are similar workers paid differently?*, MIT press, 2005.

Moscarini, Giuseppe and Fabien Postel-Vinay, "Stochastic search equilibrium," *Review of Economic Studies*, 2013, *80* (4), 1545–1581.

_ **and** _ , "Wage posting and business cycles," *American Economic Review*, 2016, *106* (5), 208–13.

_ **and** _ , "The cyclical job ladder," *Annual Review of Economics*, 2018, *10*, 165–188.

_ **and** _ , "The job ladder: Inflation vs. reallocation," *Working paper, NBER*, July 2023.

Mukoyama, Toshihiko, "The cyclicality of job-to-job transitions and its implications for aggregate productivity," *Journal of Economic Dynamics and Control*, 2014, *39*, 1–17.

Nakamura, Alice, Emi Nakamura, Kyle Phong, and Jón Steinsson, "Worker reallocation over the business cycle: evidence from Canada," *mimeo*, June 2020.

Postel-Vinay, Fabien and Alireza Sepahsalari, "Labour mobility and earnings in the UK, 1992–2017," *The Economic Journal*, 2023, *133* (656), 3071–3098.

Ridder, Geert and Gerard J Van den Berg, "Measuring labor market frictions: a cross-country comparison," *Journal of the European Economic Association*, 2003, *1* (1), 224–244.

Shimer, Robert, "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148.

Tjaden, Volker and Felix Wellschmied, "Quantifying the Contribution of Search to Wage Inequality," *American Economic Journal: Macroeconomics*, Jan 2014, *6* (1), 134–161.

Online Appendix

Contents of Paper, Appendix (A) and Online Appendix (OA)

1 Introduction **1**

2 Measurement and validation **6**

2.1 Accounting framework 6
2.2 Transitions between unemployment and employment 8
2.3 Implementation 8
2.4 Validation 8
2.5 Other estimates of EE mobility in Europe 10

3 Data **11**

4 EE mobility in Europe and the US **12**

4.1 Cross-country variation in steady-state transitions 13
4.2 Time-series variation in transition rates 16
4.3 Summary and relation to existing evidence 22

5 Insights from the job-ladder framework **23**

5.1 The job-ladder model 24
5.2 Cross-country steady-state variation 25
5.3 Time variation in the employed job-offer arrival rate 26
5.4 Job-ladder reallocation and wage inflation 28
5.5 Summary and relation to existing evidence 32

6 Conclusion **33**

A.1 Measurement of transition rates **35**

A.1.1 Definition of spells with duration less than one month 35
A.1.2 The missing duration problem 36
A.1.3 Monthly transitions at quarterly frequency 37

A.2 Additional data **38**

A.2.1 US transition rates data 38
A.2.2 Data on price and wage inflation 39

OA.1 Estimates of EE mobility for European countries **3**

OA.2 Stocks of individuals in spells with duration less than one month 4

OA.3 Missing durations 5

OA.4 Validation 6

OA.4.1 UK longitudinal monthly estimates 6

OA.4.2 Portugal and UK longitudinal quarterly estimates 6

OA.4.3 Eurostat nonemployment and unemployment transitions 11

OA.4.4 Relative EE mobility in DHS 14

OA.5 The separation rate to unemployment 22

OA.6 Frictional wage dispersion 25

OA.6.1 Mean-min ratio 25

OA.6.2 Calibration 26

OA.6.3 Quantitative results 26

OA.7 Additional results 28

OA.8 Insights from the job-ladder model using the transitions rate from employment to unemployment 28

OA.8.1 Cross-country variation 29

OA.8.2 Time variation in the employed job-offer arrival rate 29

OA.8.3 Job-reallocation and wage inflation 30

OA.1 Estimates of EE mobility for European countries

The purpose of this section is to provide a more detailed description of competing approaches to measure aggregate EE transitions for European countries.

Jolivet et al. (2006) estimate average EE transitions over an interval of a few years in the 1990s for some European countries and the US. They provide both structural and nonparametric estimates using individual duration and longitudinal data from the European Community Household Panel (ECHP). Their nonparametric estimates are not conditional on any structural assumption, while their structural estimates are based on the job-ladder model of Burdett (1978) augmented to allow for reallocation shocks, and rely on longitudinal wage data to secure identification. In addition to the fact that my estimates rely on a larger sample, have a higher frequency, and focus on a longer and more recent time period, another difference relative to Jolivet et al. (2006) is that they rely on information on job (as opposed to employer) and nonemployment spells at all durations, whereas I only use spells with duration less than one month.

Engbom (2021) and Donovan et al. (2023a) estimate EE transitions using labor force survey data covering several European countries and a similar time period as those covered in my paper. They produce respectively annual and quarterly estimates at an annual frequency using respectively microdata from long (e.g. the US Panel Data on Income Dynamics and the European Union Statistics on Income and Living Conditions) and short panels (e.g CPS and EULFS). Engbom (2021) uses data from the ECHP, its successor, the European Union Statistics on Income and Living Conditions (EU-SILC), the US Panel Data on Income Dynamics, the German Socio-Economic Panel and the British Household Panel Survey. The EU-SILC covers the same European countries, but differs from the EULFS in the following important respects: 1) for the purposes of measuring EE transitions, the frequency of the survey is yearly, 2) the sample sizes are considerably smaller, and 3) the degree of harmonization is higher, because it is based on a fully harmonized questionnaire. Engbom (2021)'s measure of the EE transition probability is defined as the share of employees who started working for their current employer at some point in the past 11 months among individuals who were in employment in each of the past 12 months.[41] Therefore, the EE transition rate that he estimates is annual — for each individual, at most one change of employer is counted in a calendar year — and it is measured at a yearly frequency. Donovan et al. (2023a) measure quarterly EE transitions using EULFS microdata and microdata provided by countries' national statistical offices. Until 2019 Eurostat did not officially release the individual identifiers in the EULFS microdata, but they were available for some countries across quarters within the same calendar year, allowing them to measure transitions for some countries, but not for the first quarter of the year.[42] After 2019

[41] The information on the start of employment with the current employer and the employee's labor market history over the past 11 months are retrospectively reported by surveyed individuals.

[42] As they explain '*Eurostat does not make the data with longitudinal identifiers available to researchers. However, roughly half of EU countries use consistent household and person identifiers within some or all years, which makes it possible to match people across quarters within a calendar year.*' Donovan et al. (2023a), p. 44.

all longitudinal identifiers are excluded from the microdata. That issue does not arise when using data from the national statistical offices. They define the EE transition probability as the share of individuals with an employer spell (tenure) less than three months among individuals who were employed across two consecutive quarters. To do so, they link individual observations across two consecutive quarters and weigh them using post-stratified cross-sectional weights. Their post-stratification procedure aims to address concerns with potential nonrandom attrition, which is a well-known problem in the labor dynamics literature. In sum, they measure quarterly transitions at a quarterly frequency.[43]

To conclude this section, and in the interest of offering the reader some critical perspective on how my estimates differ from those in Engbom (2021) and Donovan et al. (2023a), I highlight a few potentially important points. First, if cross-employer mobility takes place at a high-frequency (say weekly), the lower the frequency of measurement, the greater the extent of time-aggregation bias. Second, all three approaches rely on individuals' reported elapsed durations. These report durations are exposed to potential recall and inaccuracy biases. 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. Third, labor force surveys, like the CPS and most European national labor force surveys, are address-based. If, when individuals' change employer, they also change their address, longitudinal estimates will be exposed to attrition bias. Fourth, transitions estimates are usually quite noisy. In general, the higher the frequency of measurement, the higher the extent of statistical noise. This usually calls for some adjustment to remove/smooth noise. For example, many researchers aggregate CPS monthly transitions to the quarterly frequency, e.g. Shimer (2012). Last, my approach is suited to measure aggregate transitions (although it also works to estimate transition by subgroups, e.g. defined by gender or age), whereas their approaches also allow transitions to be defined at a finer level (e.g. between paid employment and self-employment).

OA.2 Stocks of individuals in spells with duration less than one month

As an alternative to my baseline 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

[43] In their paper, they display results as yearly averages of quarterly transitions. I suppose they do this because they cannot measure transitions for the first quarter of the year for those countries where they use EULFS microdata.

equal to the stock with duration equal to zero months. To see this more clearly, take the stock of nonemployed for less than one month. The survey questions elicit the calendar month of individuals' last employment spell. Under the alternative assumption, an individual surveyed in any week of month t with the end of her employment spell 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 were 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.[44] In sum, the data seem to favor my baseline assumption against the alternative assumption.

OA.3 Missing durations

As mentioned in Section A.1.2 of the main text, employer spell durations are missing if either the year or/and the month when the spell started are missing (YSTARTWK and MSTARTWK). By default, the EULFS does not record the month of the start of the spell if the spell duration (in years) is greater than two. Moreover, combining information on the reference month and year (REFMONTH and REFYEAR) with the duration of the spell in years, it is possible to infer whether a spell duration is greater/lower than 0/1 months.[45] Hence, the share of observations with missing employer duration reflect mostly a missing answer to the year when the employer spell started. Combining that information, I count for every quarter and country the share of observations among employed individuals with missing employer duration, and display it as the solid line on left-hand side plots of Figure OA.1. As can be seen in the plots, that share is very small for most countries and months. However, for some countries, that share increases dramatically after the 2021 redesign (e.g. France, Sweden, Poland, Ireland, Finland).

Nonemployment spell durations are missing if either the answer to the question whether the person has a previous employment experience (EXISTPR) is missing, or if year or the month when the nonemployment spell started (YEARPR and MONTHPR) is missing. By default, the EULFS does not record the month if the spell duration (in years) is greater than two. Similar to employer spell durations, I can combine the information on the reference calendar date and the reported year of the start of the spell to impute the nonemployment spell of some

[44] A larger stock of nonemployed for less than one month raises h^{NE} and h^{EN}, and a smaller short-tenure stock lowers h^{S}. Put together, those changes imply a lower h^{EE}.

[45] For example, for individuals for whom MSTARTWK is missing, but not YSTARTWK, and REFYEAR-YSTARTWK $= 1$ and REFMONTH> 1, one can be sure they have a employer spell duration longer than one month. Similarly, for individuals for whom MSTARTWK is missing, but not YSTARTWK, and REFYEAR-MSTARTWK $= 0$ and REFMONTH< 2, one can be sure they have a nonemployment duration shorter than one month.

observations. Doing so, I obtain the share of observations among the nonemployed with missing nonemployment duration, and display it as the solid line on the right-hand side plots of Figure OA.1. Similar to employer spell durations, the share of observations with missing duration is small for most quarters and countries up to 2020, and it increases sharply for some countries with the introduction of the 2021 redesign.

OA.4 Validation

This section describes the validation exercises summarized in Section 2.4 of the paper.

OA.4.1 UK longitudinal monthly estimates

Postel-Vinay and Sepahsalari (2023) combine information from the British Household Panel Survey and the UK Household Longitudinal Study (also known as Understanding Society) to measure monthly aggregate transitions rates at a monthly frequency using a longitudinal approach. One of the main reasons for them to use those data sources instead of the UK Labor Force Survey is the possibility to measure transitions at a monthly frequency. Since their paper provides a very clear discussion of the pros and cons of the two data sources, I refer the reader to their paper.

Figure OA.2 displays my estimates of the EE transition rate along the one shown in Figure 3 of Postel-Vinay and Sepahsalari (2023) over a common time period and based on a similar sample. Given the differences between the surveys (e.g. sample size and rotation, interview mode, etc.) there is no reason to expect the two series to align exactly. Nonetheless, visual inspection of Figure OA.2 clearly indicates that, not only do the series lead to the same qualitative conclusions regarding the evolution of EE mobility in the UK during the sample period (secular decline, sharp fall around the Great Recession and sluggish recovery thereafter), but also to very similar quantitative results (the two series have almost the same levels and volatilities).

OA.4.2 Portugal and UK longitudinal quarterly estimates

In this section I compare my cross-sectional estimates with existing longitudinal estimates of employer-to-employer mobility. I can access/construct longitudinal estimates for two countries (Portugal and the UK).[46] As mentioned in Section 2.4, due to time-aggregation bias, the levels and volatilities of monthly and quarterly transition estimates are not directly comparable. An alternative is to compare the dynamics of the quarter averages of my monthly estimates with appropriately adjusted quarterly longitudinal estimates from the national labor force surveys.

Figure OA.3 reports, for Portugal and the UK, time series of the cross-sectional and longitudinal estimates of the five transition probabilities reported in this paper (viz. p^{EE}, p^{NE}, p^{EN}, p^{UE} and p^{EU}). The longitudinal estimates of the EE transition probability are obtained

[46] The UK Office of National Statistics publishes time series of aggregate transition rates based on the UKLFS on their webpage. As part of a distinct but related project (see Borowczyk-Martins and Pacini (2022)), I obtained access to the microdata from the Portuguese Labor Force Survey.

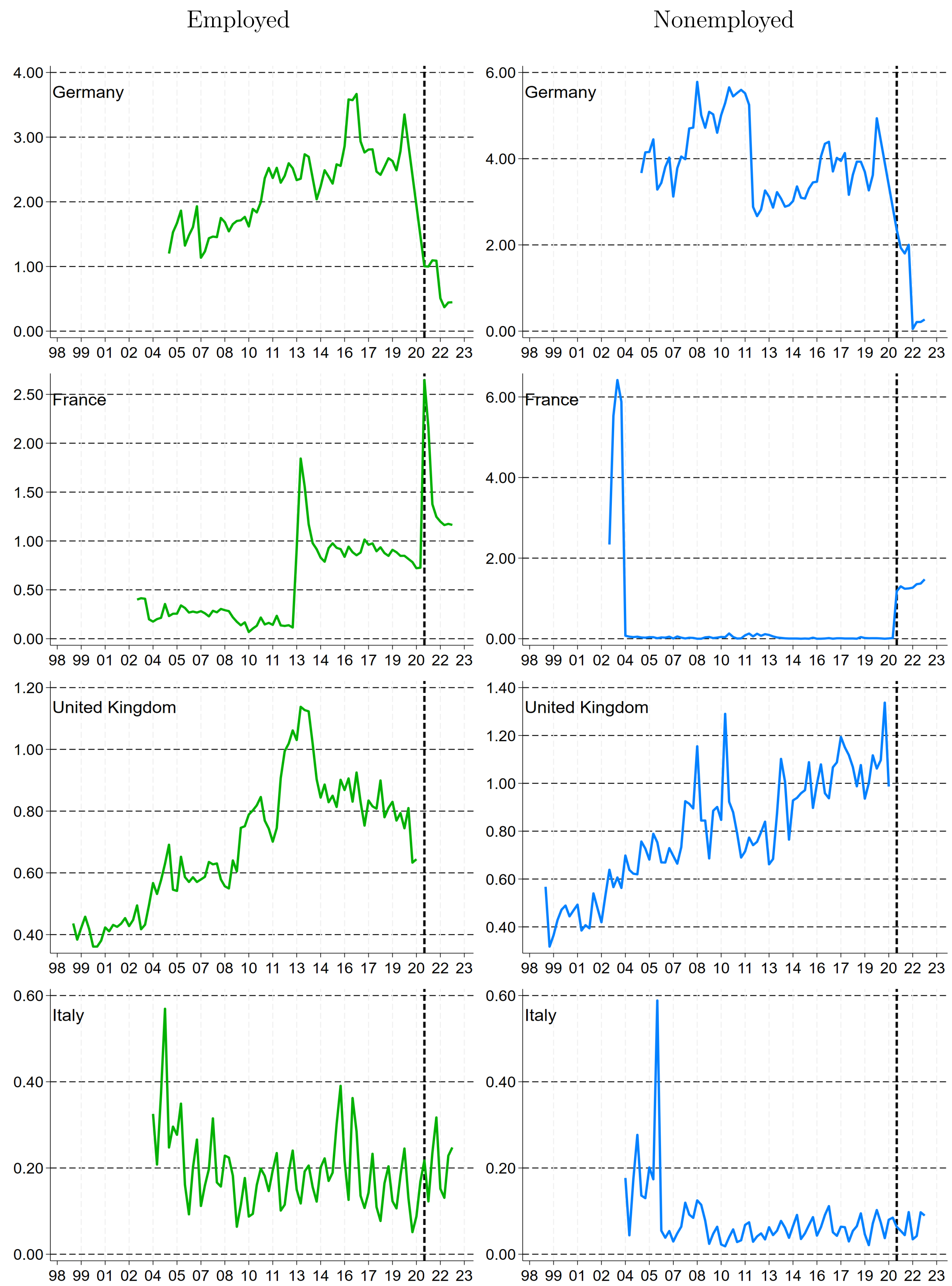

Figure OA.1: Share of observations with missing spell durations

Notes: The dashed vertical lines denote the first quarter in which the Eurostat redesign was implemented. The left-hand side plots display the share of observations with missing tenure duration. The right-hand side plots display the share of observations with missing nonemployment duration. The scale of both plots is in percent. Each time series is quarterly and uses the working-age sample (20 to 64 years old). Author's calculations based on EULFS data.

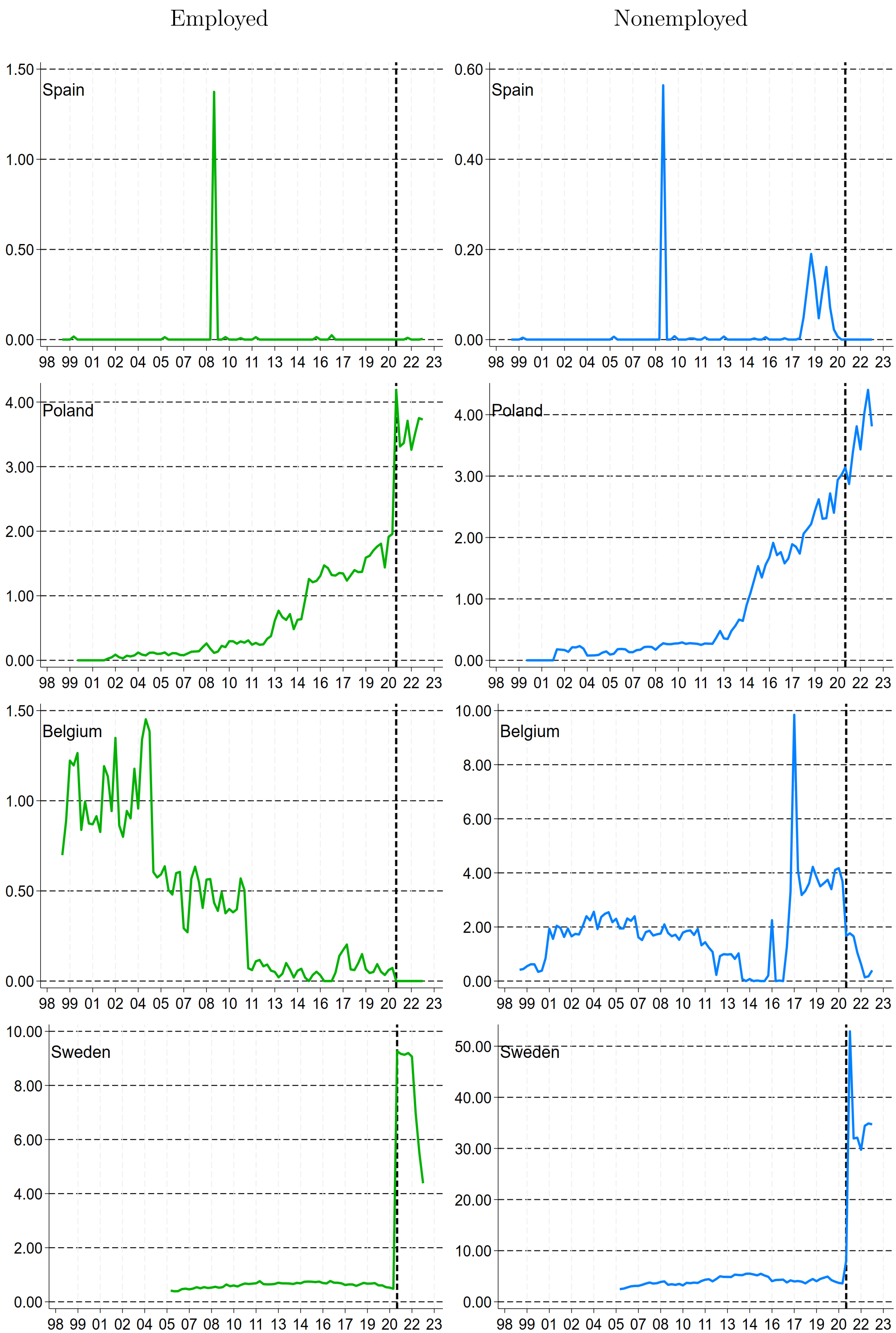

Figure OA.1 (Cont.): Share of observations with missing spell durations

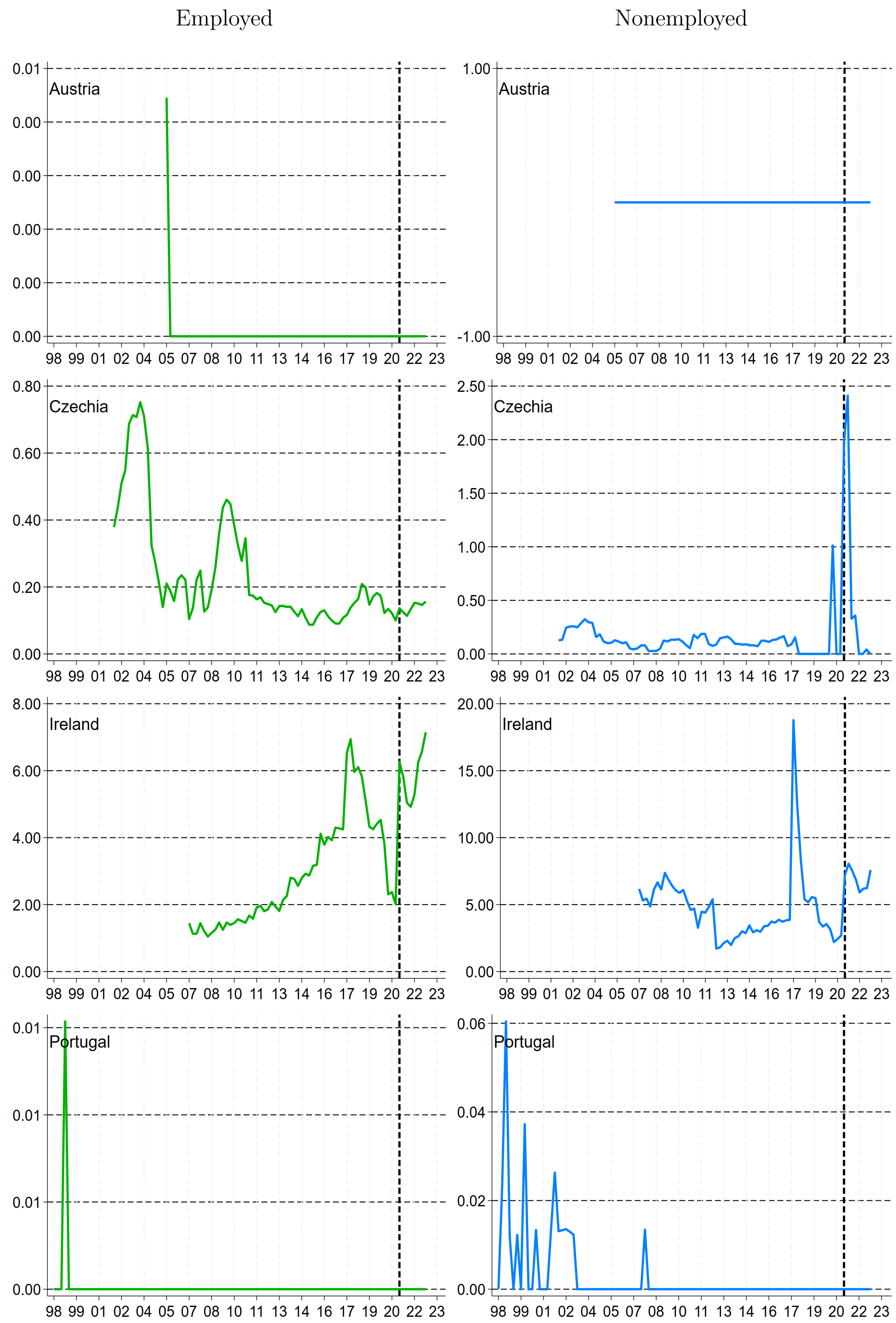

Figure OA.1 (Cont.): Share of observations with missing spell durations

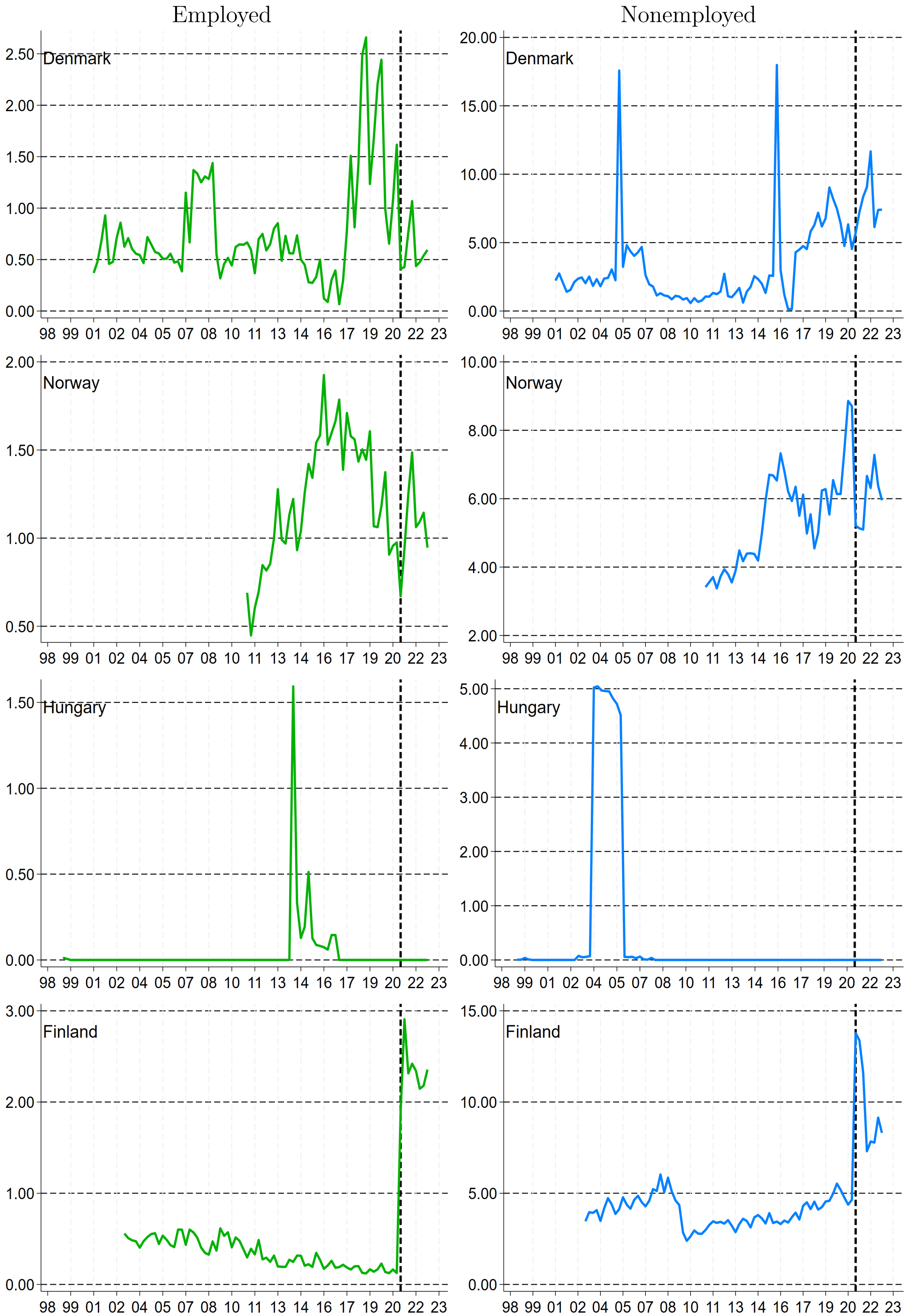

Figure OA.1 (Cont.): Share of observations with missing spell durations

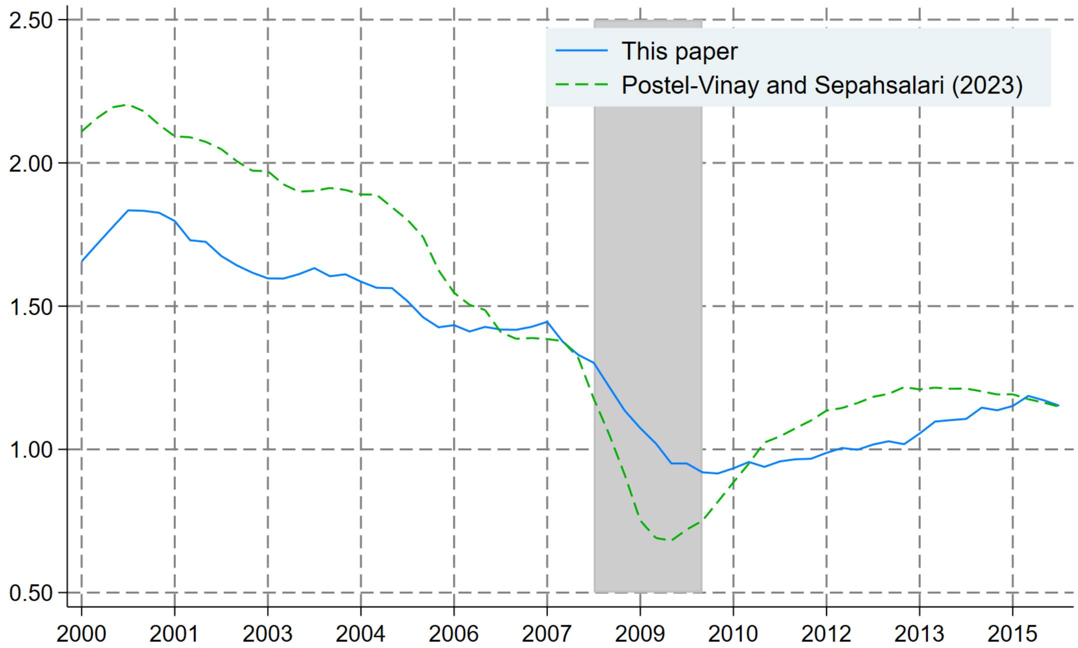

Figure OA.2: Comparison with longitudinal monthly estimates of EE transition rate

Notes: The plots displays estimates of h^{EE} produced in this paper (solid line) and in Postel-Vinay and Sepahsalari (2023) (dashed line) over 2000:1 and 2015:4 among the working age population (15 to 74 and 16 to 64 years old, respectively). Both series are quarterly averages of monthly series smoothed by a moving average filter $\mathrm{MA}(12, 1, 11)$ used in Postel-Vinay and Sepahsalari (2023).

by linking individual observations reporting to be 1) in employment across two consecutive quarters and 2) to be working for the same employer or as self-employed for less than three months. The ONS uses longitudinal weights to adjust for attrition in the UK Labor Force Survey (UKLFS). I use cross-sectional weights to compute longitudinal estimates using data from the Portuguese Labor Force Survey (PLFS).

In Figure OA.3 the cross-sectional and longitudinal estimates are respectively denoted by the solid and dotted lines. Each longitudinal estimate is adjusted to have the same mean and standard deviation as its cross-sectional counterpart. Visual inspection of the various plots of Figure OA.3 indicates the series behave similarly, especially the EE probability. The UK longitudinal series are less smooth, since they are only seasonally-adjusted by the ONS, while the cross-sectional series are filtered by a trailing moving average.

OA.4.3 Eurostat nonemployment and unemployment transitions

Eurostat publishes time series of quarterly transition probabilities across employment, unemployment and inactivity for almost all countries surveyed by the EULFS starting in the second quarter of 2010 (see link).[47] Those estimates are obtained by a longitudinal approach, since Eurostat staff can access the panel version of the EULFS. Using those data I can construct time series of quarterly transitions in and out of nonemployment (p^{NE} and p^{EN}) and unemployment (p^{UE} and p^{EU}). Following the same logic as in the previous subsection, I adjust the longitudinal

[47] Unfortunately not for all countries. For example, the time series for Germany start in the first quarter of 2021.

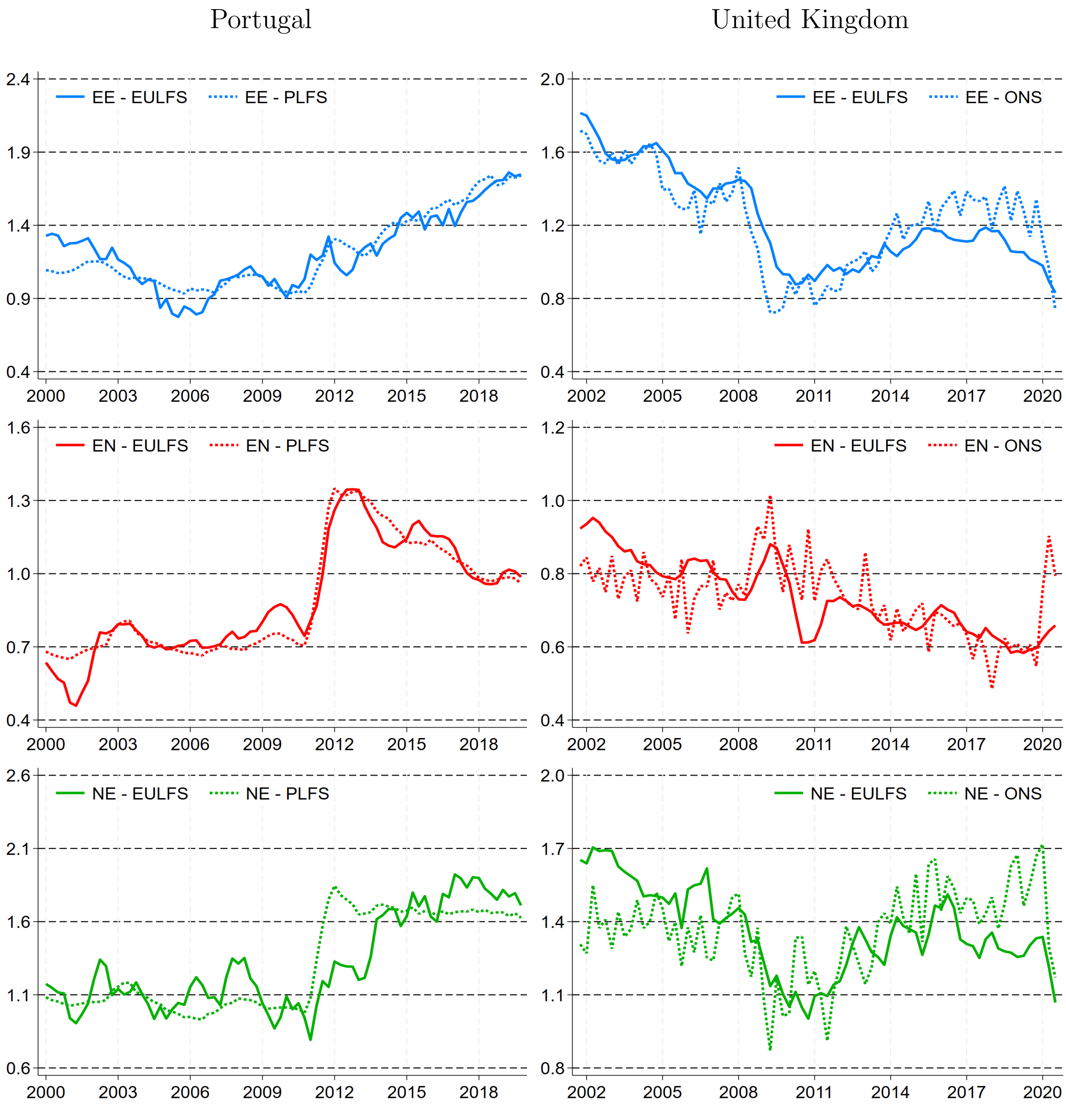

Figure OA.3: Comparison between longitudinal and cross-sectional estimates

Notes: ONS (PLFS) longitudinal time series cover individuals aged between 16 to 64 (15 to 74) years old from 2001:q1 to 2020:q4 (2000:1 to 2019:4). Each longitudinal estimate is adjusted to have the same mean and standard deviation as its cross-sectional counterpart. The cross-sectional estimates are quarter averages of the monthly series filtered by a 12-month trailing moving average, and cover individuals aged 15-74 years-old. Author's calculations based on EULFS, PLFS and ONS data.

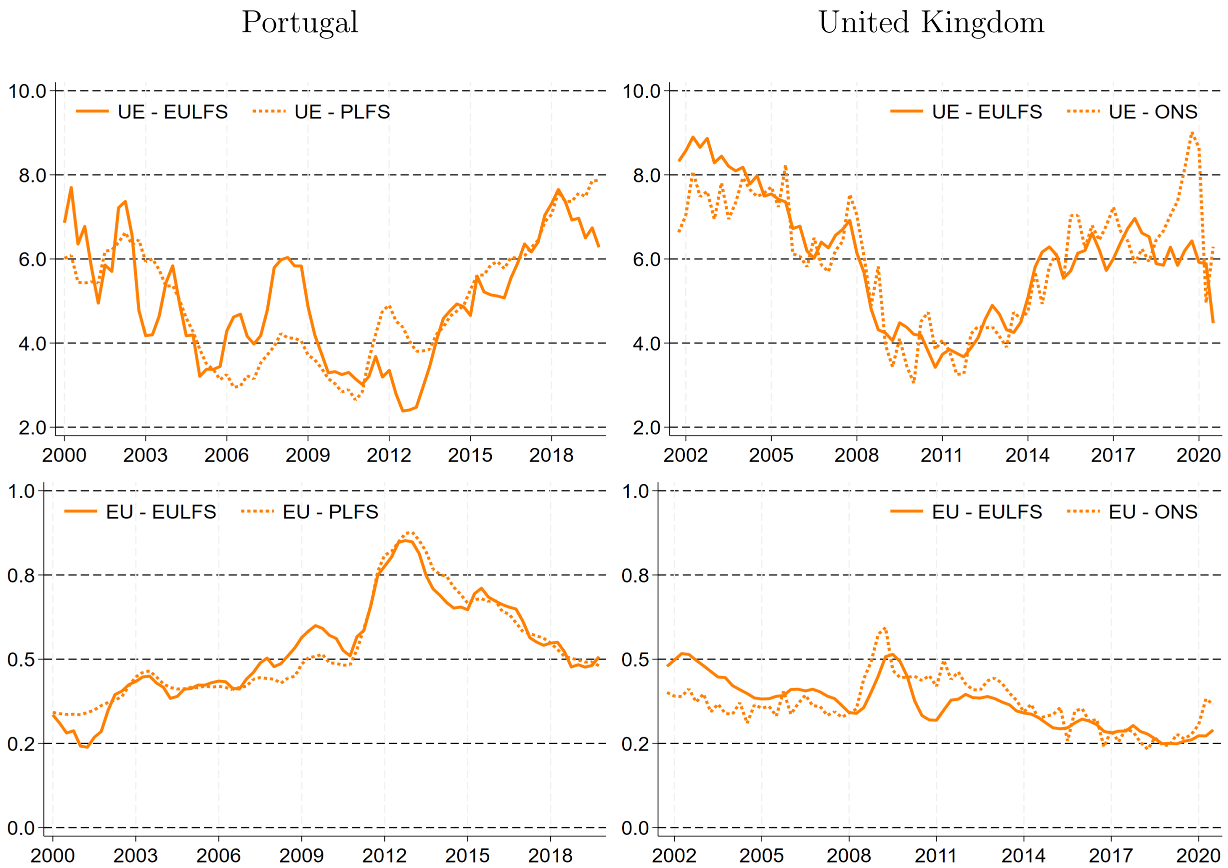

Figure OA.3 (Cont.): Comparison between longitudinal and cross-sectional estimates

estimates to render them comparable to the cross-sectional estimates.

Figures OA.4 and OA.5 report, for the available countries, the cross-sectional and longitudinal estimates, respectively denoted by the solid and dotted lines.[48] Each longitudinal estimate is adjusted to have the same mean and standard deviation as its cross-sectional counterpart. An analysis of the various time series leads to two broad conclusions. First, prior to 2021 the two series reasonably well for most countries. Second, after 2021 there is substantial discrepancy between the behavior of the two series in many countries.

As I wrote in Section 2.4 of the main text, the redesign of the EULFS implemented in the first quarter of 2021 is the likely cause of this discrepancy. Specifically, the redesigned survey forces respondents to, when asked about whether they have a previous employment experience, choose between *never have been employed* and *employment experience is limited to occasional work*. In the version of the survey that ran from the late 1990s until 2020, the two categories were bundled in the same answer. Fortunately, it is possible to use the redesigned version of the answers collected in the variable EXISTPR to implement a common measurement concept across the 2021 redesign. However, the redesigned has led to a dramatic increase in the number of missing answers to that question in many countries. I suspect this is the cause of the discrepancy. In light of this tentative conclusion, and until new data allows one to get a better sense of the underlying cause between the discrepancy in those countries, I think the

[48] I exclude the UK, for which I provide two comparisons in the previous two sections. I exclude Germany due to the very small span of the time series (two years).

best course of action is to remove observations from 2021 and beyond from the analysis.

Figure OA.4: Comparison Eurostat nonemployment longitudinal estimates

Notes: The dashed vertical lines denote the first quarter in which the Eurostat redesign was implemented. Eurostat longitudinal time series are denoted by dots and cover individuals aged between 15 to 74 years old from 2010:4 to 2022:4. Each longitudinal estimate is adjusted to have the same mean and standard deviation as its cross-sectional counterpart. The cross-sectional estimates are denoted by triangles, are quarter averages of the monthly series filtered by a 12-month trailing moving average, and cover individuals aged 20-64 years-old. Author's calculations based on EULFS and Eurostat data.

OA.4.4 Relative EE mobility in DHS

In this section I compare the estimates of relative mobility displayed in the fourth column of Table 2 with comparable numbers computed using Donovan et al. (2023a)'s annual averages of

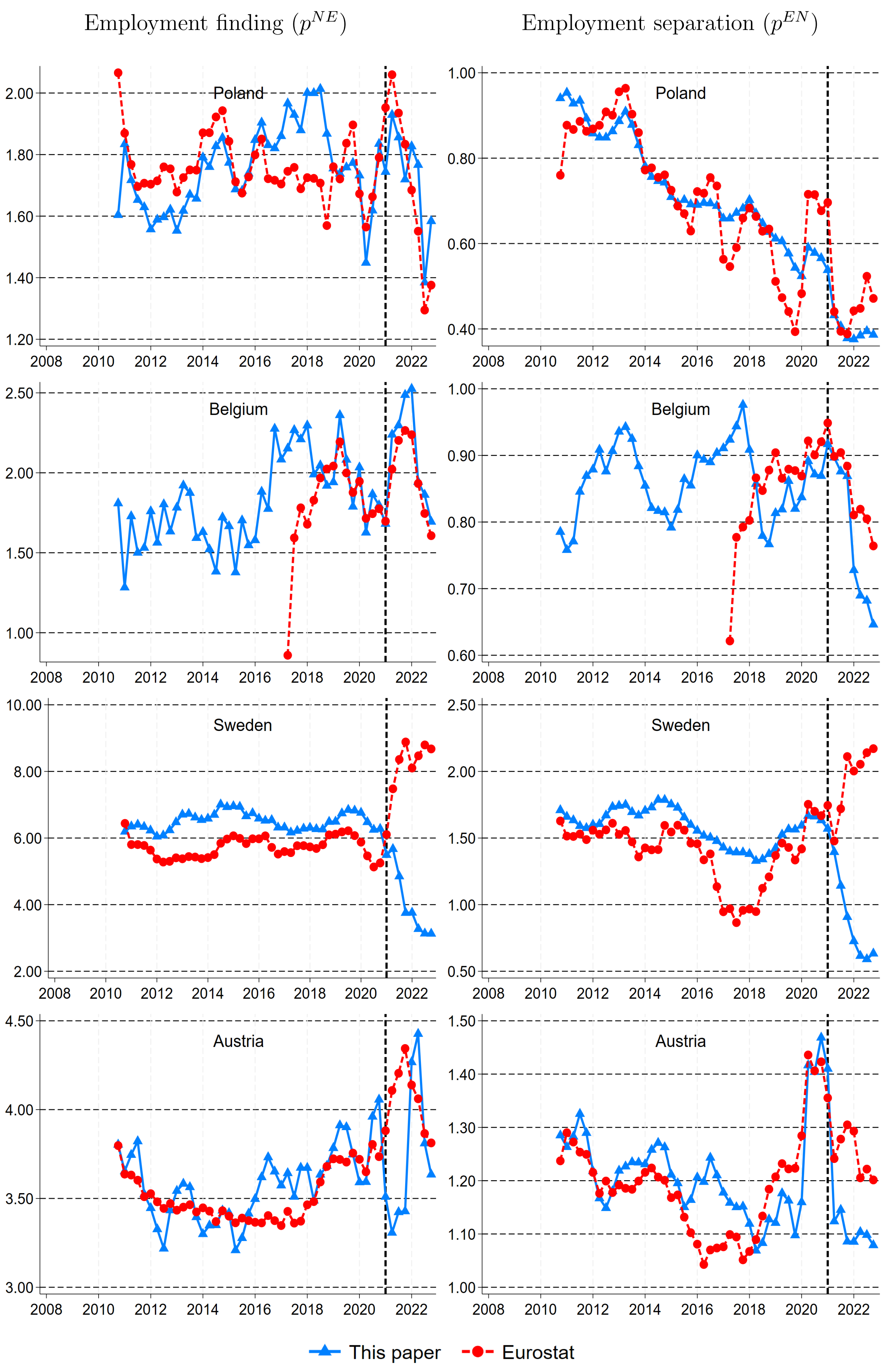

Figure OA.4 (Cont.): Comparison Eurostat nonemployment longitudinal estimates

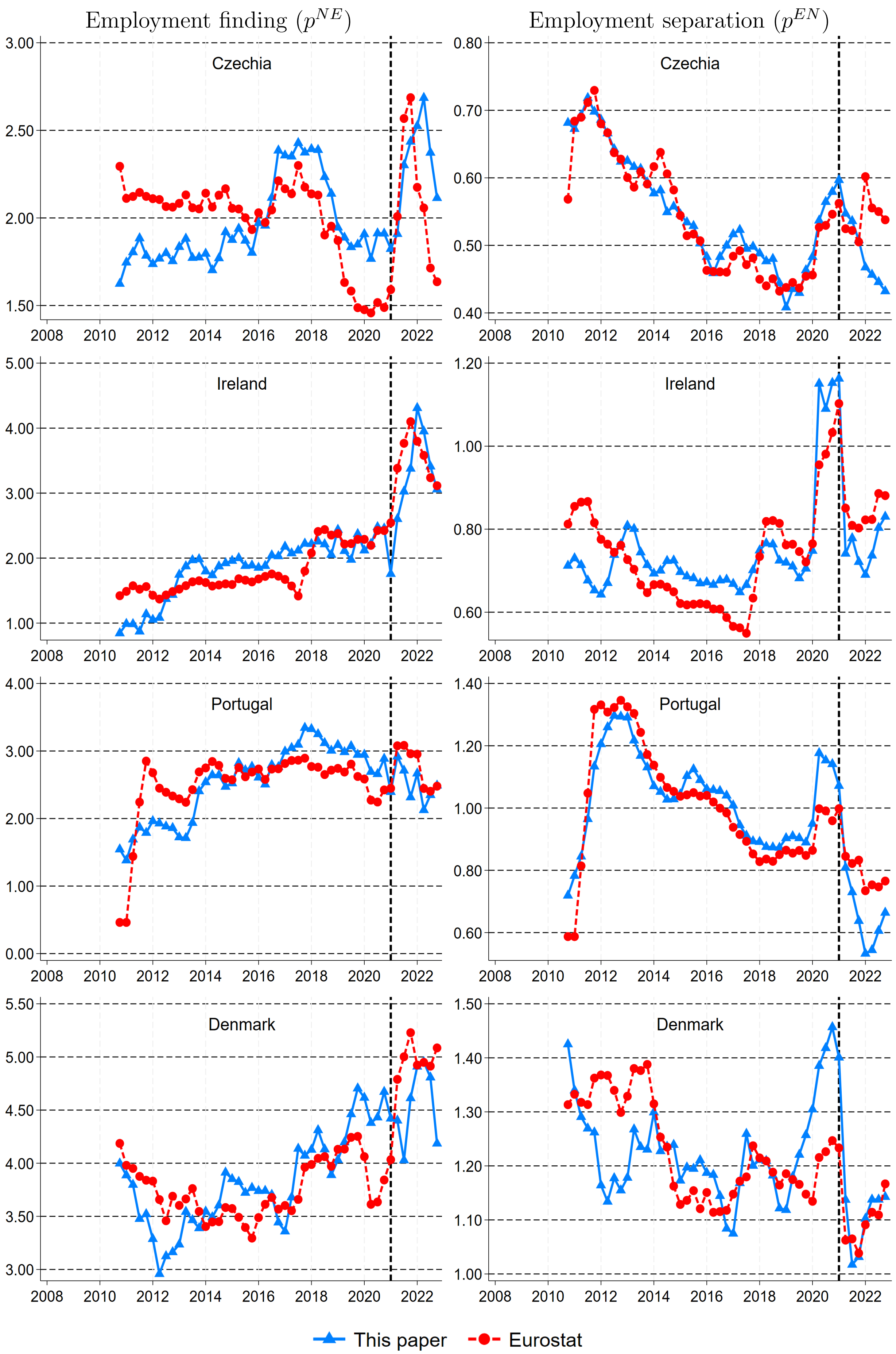

Figure OA.4 (Cont.): Comparison Eurostat nonemployment longitudinal estimates

Employment finding (p^{NE}) Employment separation (p^{EN})

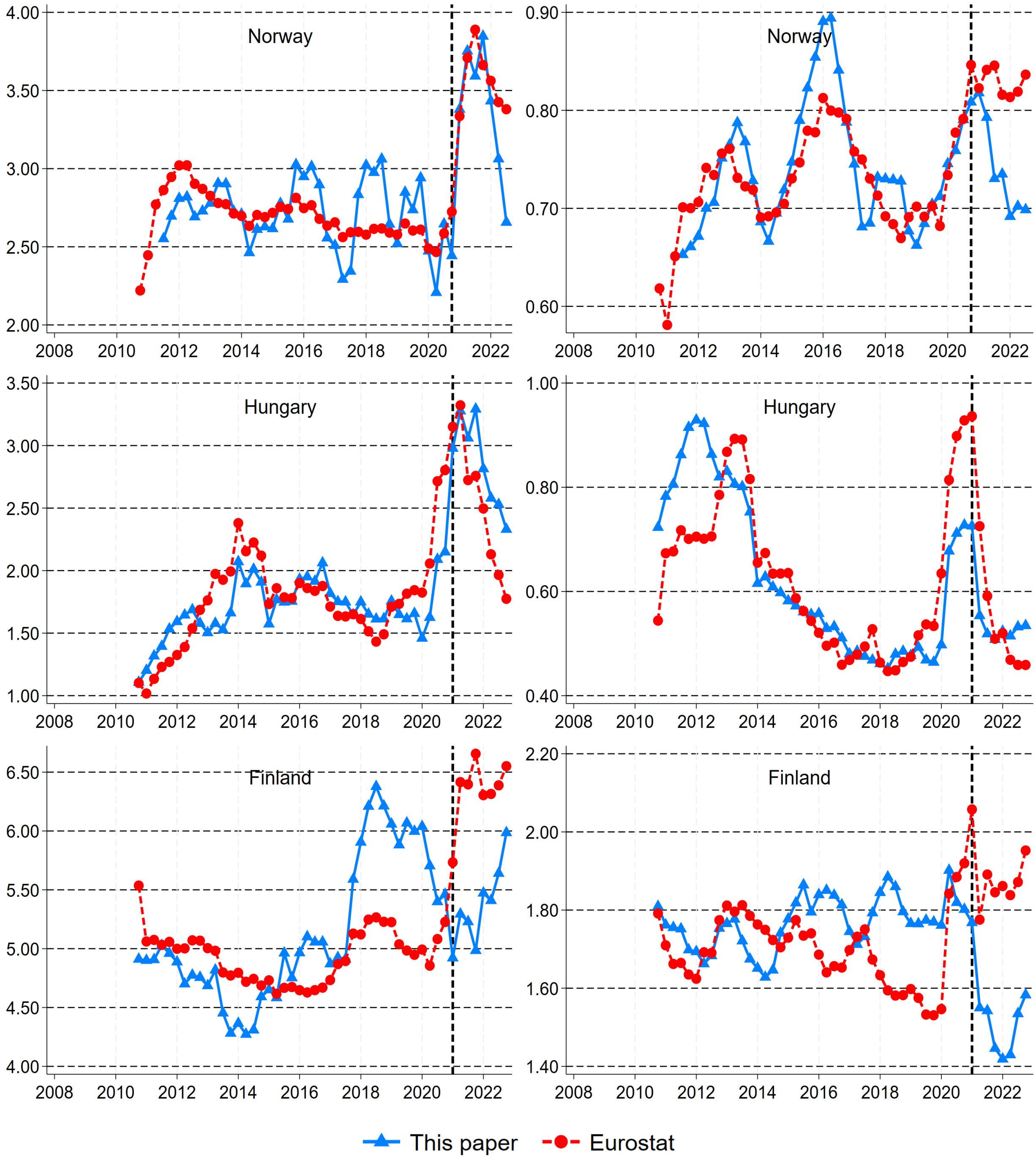

Figure OA.4 (Cont.): Comparison Eurostat nonemployment longitudinal estimates

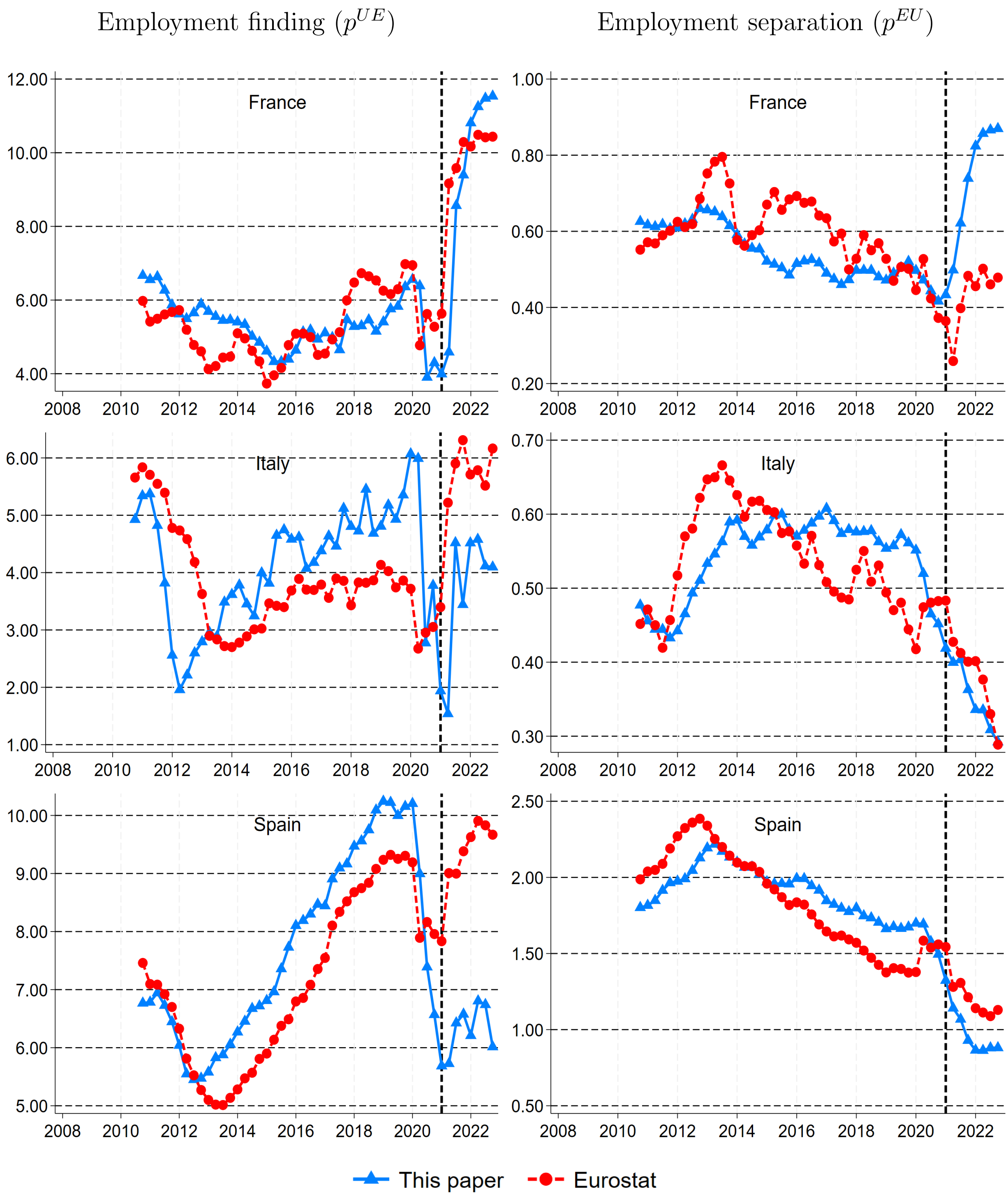

Figure OA.5: Comparison Eurostat unemployment longitudinal estimates

Notes: The dashed vertical lines denote the first quarter in which the Eurostat redesign was implemented. Eurostat longitudinal time series are denoted by dots and cover individuals aged between 15 to 74 years old from 2010:4 to 2022:4. Each longitudinal estimate is adjusted to have the same mean and standard deviation as its cross-sectional counterpart. The cross-sectional estimates are denoted by triangles, are quarter averages of the monthly series filtered by a 12-month trailing moving average, and cover individuals aged 20-64 years-old. Author's calculations based on EULFS and Eurostat data.

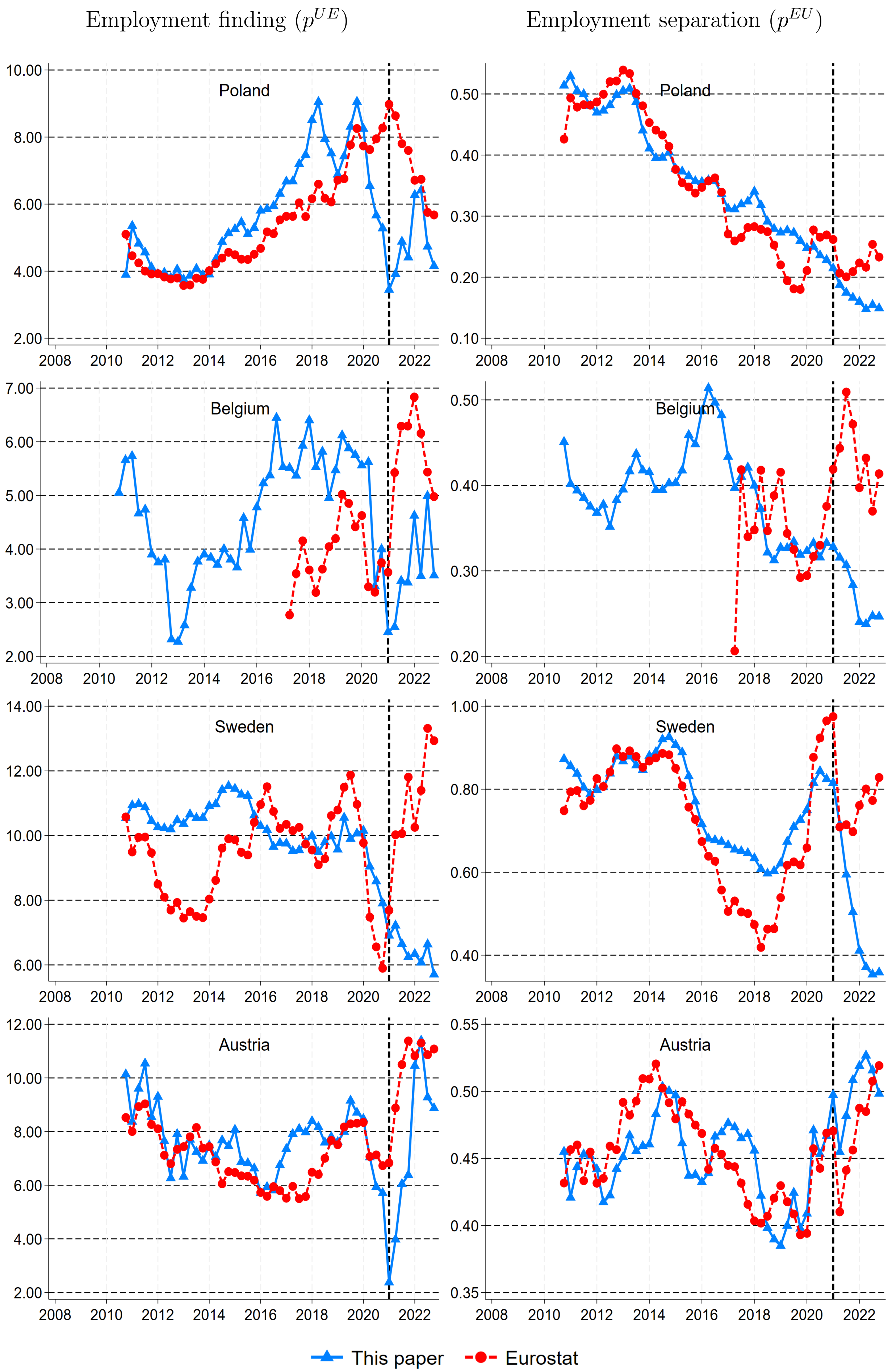

Figure OA.5 (Cont.): Comparison Eurostat unemployment longitudinal estimates

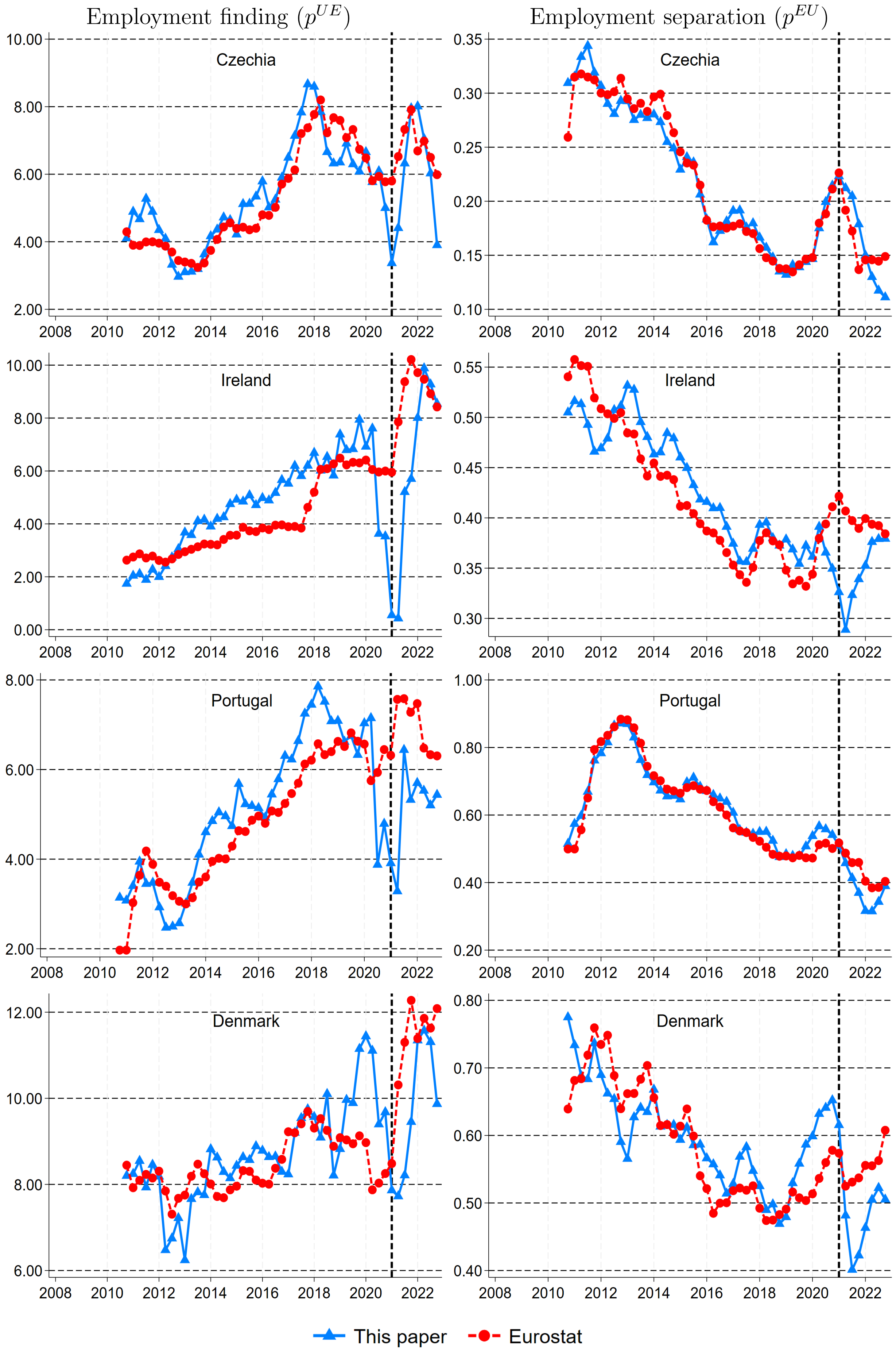

Figure OA.5 (Cont.): Comparison Eurostat unemployment longitudinal estimates

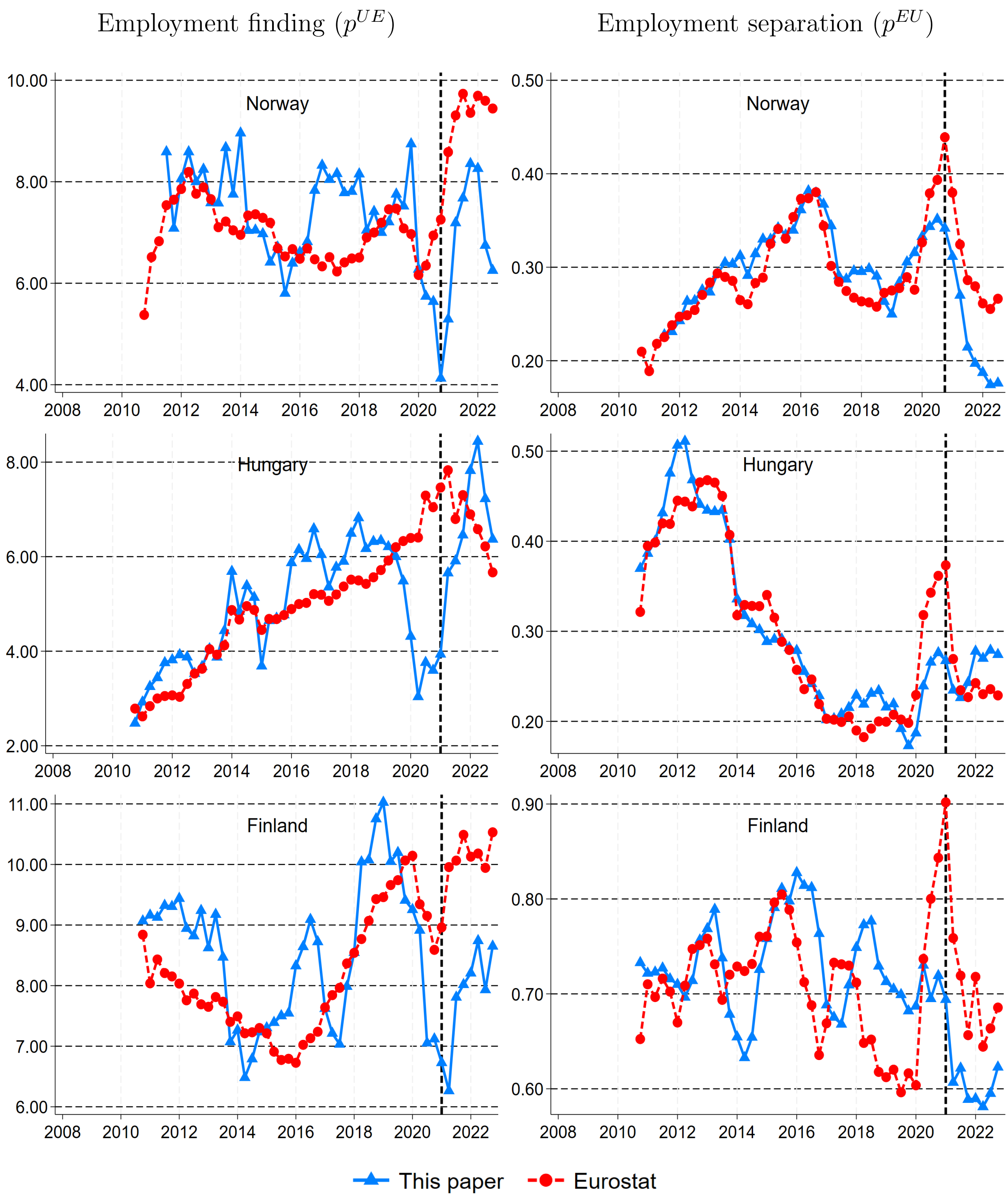

Figure OA.5 (Cont.): Comparison Eurostat unemployment longitudinal estimates

quarterly estimates of p^{EN} and p^{EE}.[49]

As mentioned in Section 2.4, time aggregation implies that the levels of transition probability estimates measured at different frequencies are not directly comparable. To some extent, the same logic extends to the comparison of ratios of probabilities, so this comparison is far from definitive. Nonetheless, it is useful to check whether a similar pattern of relative EE mobility is found using alternative cross-country estimates of labor turnover.

Figure OA.6 reports my estimates of relative EE mobility (measured by the ratio p^{EE}/p^{EN}) along with those calculated using Donovan et al. (2023a)'s estimates. The number of countries included in the plot is smaller than in Table 2, since it only reports countries and time periods that overlap across the two data sets. Both sets of estimates reveal large variation in relative EE mobility and, with the exception of France and Sweden, converge on the value of p^{EE}/p^{EN} for each country. Importantly, both sets of estimates place Italy and Spain at the bottom of the European sample, the value for the US is very close to Austria's, and both are well below the values of many European countries (e.g. Denmark, Poland, Portugal, the UK and Sweden).

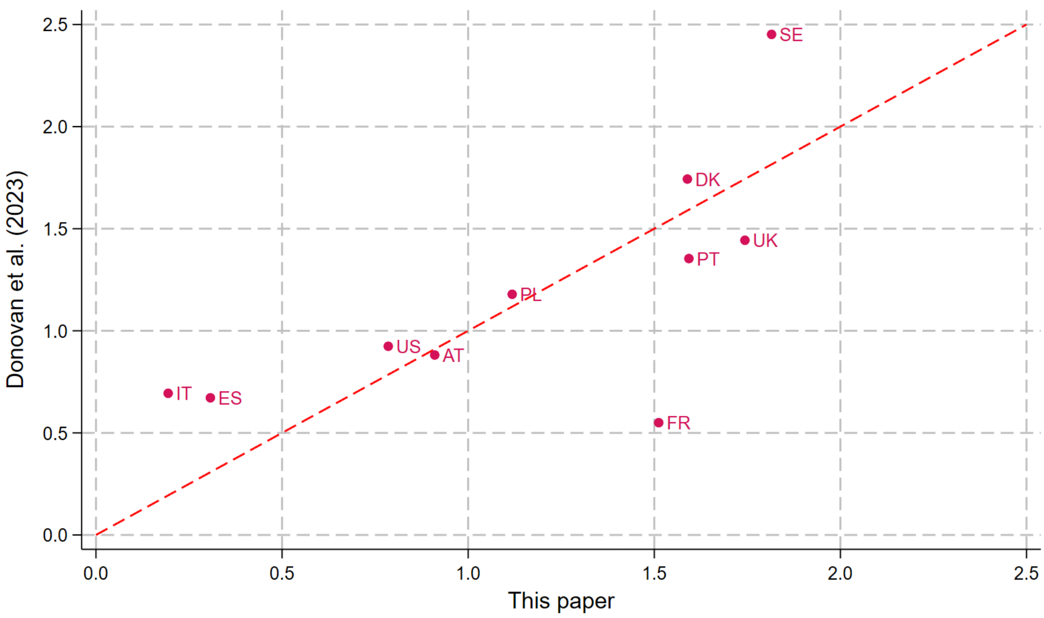

Figure OA.6: Comparison relative EE mobility Donovan et al. (2023a)

Notes: The numbers displayed on horizontal (vertical) axis are the ratio of the monthly (quarterly) transition probabilities p^{EE}/p^{EN} produced in this paper (Donovan et al. (2023a)). The dashed line denotes the 45 degrees line. Coverage: Individuals aged between 20 and 64, ratio calculated on average transitions probabilities over the years 2014 to 2019.

OA.5 The separation rate to unemployment

Figure OA.7 report time series of the two separation probabilities (p^{EN} and p^{EU}). Both separation probabilities are clearly countercylical, and in all countries there is a very tight comovement between them. In a few countries (namely Italy and Finland) p^{EN} appears more cyclical.

[49] I downloaded the data from the following webpage.

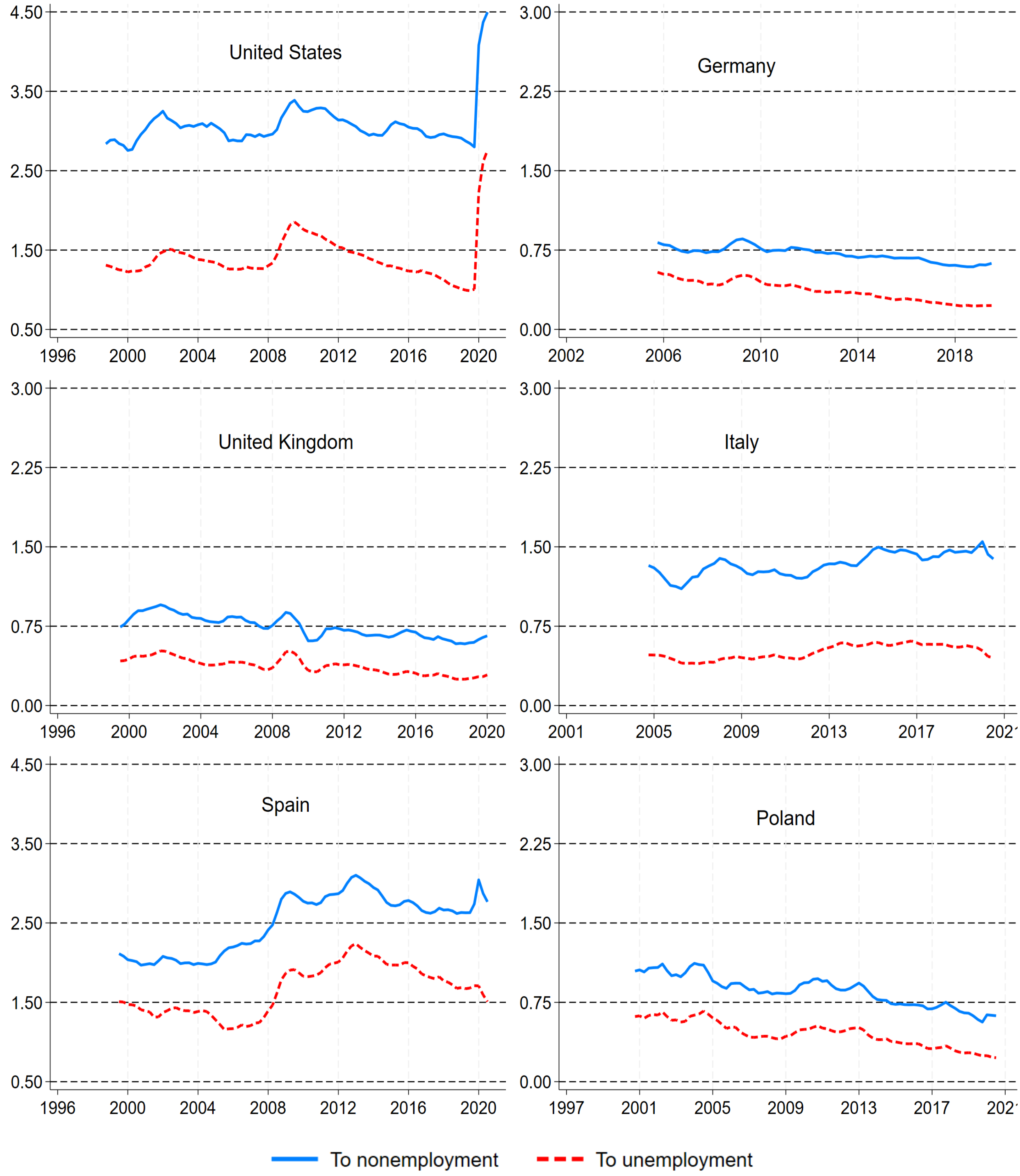

Figure OA.7: Time series of employment separation probabilities

Notes: All series are quarter averages of monthly time series smoothed by a 12-month trailing moving average, and expressed in percent. Coverage: Working-age sample from 1999:1 to 2020:4 (start and end dates differ across countries). Author's calculations based on data from the EULFS, Fujita et al. (2024) and the CPS.

Figure OA.7 (Cont.): Time series of employment separation probabilities

OA.6 Frictional wage dispersion

I use the job-ladder model described in Section 5.1 to map the differences in average turnover rates documented in Table 2 in the main text onto cross-country variation in frictional wage dispersion. Wage dispersion (the extent to which equally productive workers are paid differently) is an empirical phenomenon that has significant bearing on the performance of labor markets (e.g. their equity and efficiency). Quantifying and identifying the sources of frictional wage dispersion is one of the central goals of search models of the labor market (Mortensen (2005)). For that purpose, I employ the measure of frictional wage dispersion popularized by Hornstein et al. (2011), the ratio of the average to the minimum wage (also known as the Mean-min or Mm ratio), implied by Burdett (1978)'s job-ladder model.[50]

OA.6.1 Mean-min ratio

In the job-ladder model the ratio between the average wage ($\bar{w}$) and the reservation wage (w^*) is given by the following expression:

$$Mm = \frac{(\lambda^u - \lambda^e)/(r + \sigma + \lambda^e) + 1}{(\lambda^u - \lambda^e)/(r + \sigma + \lambda^e) + \rho}, \tag{14}$$

where ρ is the unemployment income replacement rate.

For sake of clarity, I now derive the expression for the Mm ratio. By definition the average wage is:

$$\bar{w} = \int_{w^*}^{w^{\max}} w dG(z). \tag{15}$$

This expression can manipulated to obtain the following expression for the difference between the average and the reservation wages:

$$\bar{w} - w^* = \int_{w^*}^{w^{\max}} \bar{G}(w) dz. \tag{16}$$

Since r is small relative to σ and λ^e, one can rewrite Equation (9) as

$$\bar{G}(w) \approx \frac{(r + \sigma + \lambda^e)\bar{F}(w)}{r + \sigma + \lambda^e \bar{F}(w)} \tag{17}$$

Substituting this expression in the reservation wage (Equation (8)), and writing the flow

[50] As demonstrated by Hornstein et al. (2011), the job-ladder model generates more frictional wage dispersion than the basic job-search model. Their finding that the basic job-search model can only generate very low levels of frictional wage dispersion (see Section II of their paper, namely the paragraph *A "European" Calibration*) is also present in all European countries in my sample. However, my goal is not to assess whether the calibrated model delivers levels of frictional wage dispersion that match those measured using individual wage data, or estimated with richer models and more data (see two recent examples in Tjaden and Wellschmied (2014) and Burdett et al. (2016)).

value of unemployment as $b = \rho\bar{w}$ yields:

$$w^* \approx \rho\bar{w} + \frac{(\lambda^u - \lambda^e)}{r + \sigma + \lambda^e} \int_{w^*}^{w^{\max}} \bar{G}(z)dz \tag{18}$$

Last, substitute Equation (16) into Equation (18) to obtain the expression for the Mean-min ratio

$$Mm \equiv \bar{w}/w^* \approx \frac{(\lambda^u - \lambda^e)/(r + \sigma + \lambda^e) + 1}{(\lambda^u - \lambda^e)/(r + \sigma + \lambda^e) + \rho}. \tag{19}$$

OA.6.2 Calibration

To compute the Mm ratio I calibrate the various parameters of the model using transition estimates and publicly-available data on income replacement rates of unemployed individuals. In my calibration I set λ^u to the average value of the transition from nonemployment to employment (h^{NE}) scaled by the average of the ratio p^{UE}/p^{NE} in the US from 2014 to 2019 (which is equal to 3). The idea is to scale up countries' h^{NE} by a common factor that reflects the higher labor market attachment of the unemployed. This preserves the observed cross-country differences in h^{NE} and generates plausible levels of the Mm ratio. Second, I calibrate σ to the average employment-separation rate (h^{NE}). Third, to calibrate λ^e, I combine my estimates of the average hazard rate across employers (h^{EE}) with the expression for the equilibrium average transition hazard implied by the model (Equation (12)) and the calibrated value of σ. Fourth, I set the unemployment income replacement rate equal to the average net income replacement rate of unemployed workers.[51] Last, I set the discount rate r to match an annual rate of 5%.

OA.6.3 Quantitative results

Panel a. of Table OA.1 displays the Mm ratio and its main components for the 16 European countries in my sample nd the US. The bottom row displays the sample averages. The first column reports the Mm ratio. A number of observations can be made. First, there is substantial cross-country variation in the Mm ratio. The value reported for the US, 1.4, is just above the upper limit of the range of values reported by Hornstein et al. (2011), 1.16–1.27, and lies close to the average cross-country value of 1.5. The second and third columns of Panel a. of Table OA.1 report, respectively, the average unemployment income net replacement rates (ρ) and the value of the transitions coefficient $\varphi \equiv (\lambda^u - \lambda^e)/(r + \sigma + \lambda^e)$. Both ρ and φ decrease the Mm ratio, as they push the value of the reservation wage closer to that of the average wage. Scanning the values in those columns reveals some variation in the two drivers

[51] For each country I take the average of the unemployment income replacement rate for individuals who earned the average wage in their previous job and with unemployment duration equal to two months and that differ in their family type. I use the Tax and Benefits database from the European Commission (see `https://europa.eu/economy_finance/db_indicators/tab/`). This database provides the unemployment income net replacement rate (expressed as a fraction of the income of the previous job) for individuals earning different wages (expressed as a fraction of the average wage), among groups of unemployed workers that differ in terms of their unemployment duration, family type (either single, single and have two children, live in a couple and are the single earner, or live in a couple, are the single earner and have two children).

of frictional wage dispersion. Looking at unemployment income replacement rates first, many countries have levels of ρ between 0.6 and 0.7. Hungary and the US have the lowest levels at 0.3, while Denmark has the highest value at 0.8.[52] Moving to variation in the transitions coefficient φ, it is perhaps surprising that, for some countries, φ is negative, indicating that the job-offer arrival rate is higher among the employed compared to the unemployed. This simple decomposition offers an interesting characterization of cross-country differences in labor market performance. Countries can attain the same levels of measured frictional wage dispersion using a very different policy mix, which can entail quite distinct consequences for labor market participants.[53] Consider the values for the US and Portugal displayed in Panel a. of Table OA.1, and their interpretation in the context of the job-ladder model. The value of Mm is the same, but while the US attains such level by combining low unemployment income replacement rates with a much higher relative search efficiency of the unemployed, Portugal offers a lot more income support to the unemployed, and greater opportunities to move up the job ladder to employed workers.

Table OA.1: Cross-country frictional wage dispersion

	a. Min-mean ratio and its components					b. Counterfactual min-mean ratios		
	Mm	ρ	φ	κ^e	κ^u	Mm^{κ^e}	Mm^{κ^u}	Mm^{ρ}
United States	1.4	0.3	1.6	2.6	8.6	1.2	1.5	1.6
Germany	1.8	0.7	-0.2	16.8	12.6	3.0	1.3	1.2
France	1.5	0.7	-0.1	8.5	7.8	1.5	1.6	1.2
United Kingdom	1.9	0.5	0.0	11.6	11.7	1.9	1.4	1.4
Italy	1.1	0.7	3.3	0.4	5.2	1.1	2.2	1.2
Spain	1.1	0.6	2.9	0.8	5.8	1.1	1.9	1.3
Poland	1.4	0.6	0.7	4.9	8.8	1.3	1.5	1.3
Belgium	1.4	0.6	0.3	5.3	7.0	1.3	1.7	1.3
Sweden	1.7	0.6	0.0	12.8	13.4	2.0	1.3	1.3
Austria	1.2	0.6	1.4	3.4	9.5	1.2	1.5	1.3
Czechia	1.3	0.6	0.6	7.6	13.1	1.5	1.3	1.3
Ireland	1.7	0.6	-0.0	10.4	10.0	1.7	1.4	1.3
Portugal	1.4	0.7	-0.0	9.6	9.2	1.6	1.5	1.2
Norway	1.3	0.7	0.3	8.4	11.3	1.5	1.4	1.2
Denmark	1.3	0.8	0.1	9.5	10.6	1.6	1.4	1.2
Hungary	2.5	0.3	0.1	9.5	10.6	1.6	1.4	1.6
Finland	1.1	0.7	1.7	2.9	9.4	1.2	1.5	1.2
Sample average	1.5	0.6	0.7	7.4	9.7	1.5	1.5	1.3

Notes: The calibrated parameters are based on average monthly transition rates for the working-age sample from 2014 to 2019 and average unemployment income replacement as described in the text. The bottom row of Panels a. and b. reports cross-country averages. Author's calculations based on data from the EULFS, Fujita et al. (2024), the CPS and the European Commission.

[52] The calibrated value of ρ for the US is close to the one used in Hornstein et al. (2011).

[53] My use of the term *policy mix* is obviously an abuse of language. In reality, countries cannot choose the job-offer arrival rates (they depend, inter alia, on search effort and labor-market policies), and income replacement rates affect the acceptance rate of unemployed workers, which is affected by opportunities to climb the job ladder.

So far, I have highlighted the extent of cross-country variation in Mm, ρ and φ. Now I want to determine which parameters are relatively more important in driving variation in Mm. For that purpose, it is useful to introduce a simpler expression for the Mm ratio. Starting from Equation (14), let $r \to 0$, $\kappa^e \equiv \lambda^e/\sigma$ and $\kappa^u \equiv \lambda^u/\sigma$.[54] Then:

$$Mm = \frac{(\kappa^u - \kappa^e)/(1+\kappa^e)+1}{(\kappa^u - \kappa^e)/(1+\kappa^e)+\rho}. \tag{20}$$

Equation (20) fleshes out the distinct impact of κ^u and κ^e on frictional wage dispersion: κ^u decreases the Mm ratio, while κ^e increases it. In general, as was the case for ρ, higher values of κ^u imply lower Mm ratios, as they push the reservation wage closer to the average wage. On the other hand, as show in Equation (10) in the main text, higher values of κ^e raise the Mm ratio by moving the average wage away from the reservation wage. The fourth and fifth columns of Panel a. of Table OA.1 display the values for those two coefficients. The extent of cross-country differences in the relative turnover rates κ^u and κ^e is large, and there is a clear positive association between them. Focusing on the US, its value of κ^u is similar to that of many European countries, but its value of κ^e is much lower. Indeed, similar to the patterns of relative EE mobility documented in Table 2, Italy, Spain and the US have the lowest values of κ^e, well below the sample mean of 7.4. On the other hand, while Italy and Spain also have very low levels of κ^u, those of the US are just below the cross-country mean (8.6 vs 9.7, respectively). To get a sense of the quantitative importance of cross-country differences in κ^e in accounting for differences in Mm ratios, the first column of Panel b. of Table OA.1 reports a counterfactual Mm ratio calculated using the cross-country averages of κ^u and ρ and the country-specific value of κ^e. The two last columns of Panel b. of Table OA.1) report similar counterfactual Mm ratios based on variation in κ^u and ρ, respectively. For most countries, the values of Mm and Mm^{κ^e} are closer to each other than either Mm^{κ^u} or Mm^{ρ}. More importantly, Mm^{κ^e} matches the cross-country variation in countries' actual Mean-min ratios much better than either Mm^{κ^u} or Mm^{ρ}.

OA.7 Additional results

OA.8 Insights from the job-ladder model using the transitions rate from employment to unemployment

This section repeats the analysis in Section 5 using the transition rate from employment to unemployment.

[54]Since $r = 0.0041$ at a monthly frequency, it is a order of magnitude lower than $h^{EE} + h^{EN} = \sigma + \lambda_e$. See Panel a. of Table OA.1 and note that $p^{EE} + p^{EN} \approx h^{EE} + h^{EN}$.

Table OA.2: Wage Phillips correlations at different lags

	L0	L1	L2	L3	L4
United States	0.69	0.65	0.60	0.57	0.49
Germany	0.42	0.47	0.52	0.53	0.52
United Kingdom	0.35	0.26	0.19	0.19	0.25
Italy	0.45	0.47	0.54	0.59	0.59
Spain	0.56	0.60	0.64	0.65	0.68
Poland	0.39	0.56	0.61	0.64	0.64
Belgium	0.34	0.49	0.59	0.55	0.46
Sweden	0.34	0.31	0.33	0.30	0.22
Austria	0.07	0.16	0.13	-0.02	-0.14
Czechia	0.65	0.61	0.53	0.49	0.41
Portugal	0.47	0.45	0.44	0.41	0.38
Denmark	0.38	0.45	0.53	0.49	0.49
Hungary	0.01	0.04	0.03	0.03	0.03
Finland	-0.02	-0.12	-0.12	-0.21	-0.26

Notes: The table reports correlation coefficients between wage inflation and the job-ladder reallocation index at different lags (where L1 stands for the first lag, etc.). The job-ladder reallocation index series are calculated by the author using data from the EULFS, Fujita et al. (2024) and the CPS, and are quarter averages of the monthly series filtered by a 12-month trailing moving-average. The wage inflation time series are taken from the US Bureau of Labor Statistics and Eurostat, and are expressed as first-differences of the logged seasonally-adjusted compensation per hour index measured at quarterly frequency, and subsequently smoothed by a four-quarter trailing moving average. Coverage: Working-age sample from 1999:1 – 2019:4 (starting dates differ across countries).

OA.8.1 Cross-country variation

In this subsection I show that, when I use the transition rate from employment to unemployment to calibrate the job-ladder model, I obtain similar conclusions regarding cross-country differences in the speed with which workers climb up the job ladder as those obtained using the transition rate from employment to nonemployment. Table OA.3 is the counterpart to Table 4 in the main text. The last column reports the value of the job-reallocation index. The levels are of course very different to those reported in Table 4, but the differences across countries are similar. Italy, Spain, the US, Finland and Austria display levels well below the sample mean, whereas Germany, Sweden and the UK exhibit levels very much above the sample average.

OA.8.2 Time variation in the employed job-offer arrival rate

Table OA.4 reports the correlations coefficients based on the value of λ^e obtained using the transition rate from employment to unemployment to calibrate the job-destruction rate. The patterns are strikingly similar to those reported in Table 5.3 based on the value of λ^e obtained using h^{EN} to calibrate the job-destruction rate.

Table OA.3: Job-ladder model parameters — Transition from employment to unemployment

	λ^e	σ	κ^e
United States	0.19	0.012	15.7
Germany	0.66	0.003	250.1
France	0.20	0.005	40.1
United Kingdom	0.27	0.003	98.6
Italy	0.01	0.006	1.3
Spain	0.02	0.019	1.2
Poland	0.07	0.003	22.5
Belgium	0.12	0.004	30.6
Sweden	0.92	0.007	127.0
Austria	0.11	0.004	25.7
Czechia	0.24	0.002	133.4
Ireland	0.18	0.004	45.2
Portugal	0.20	0.006	34.4
Norway	0.28	0.003	87.7
Denmark	0.44	0.006	79.2
Hungary	0.19	0.002	81.8
Finland	0.12	0.007	16.4
Sample average	0.25	0.006	64.2

Notes: The reported statistics are based on average monthly transitions from 2014 to 2019. λ_e and κ_e are calculated using the transition rate from employment to unemployment. The bottom row reports cross-country averages. Author's calculations based on data from the EULFS, Fujita et al. (2024), and the CPS. Coverage: Working-age sample.

OA.8.3 Job-reallocation and wage inflation

In this subsection I report counterparts to the results displayed in Section 5.4 but based on the transition rate from employment to unemployment. Because of the very tight comovement between p^{EN} and p^{EU} in most countries, the results are very similar. Figure OA.8 underscores this point by displaying series of the two alternative estimates of the job-ladder reallocation index in each country.

Table OA.5 is the counterpart to Table 6 in the main text. The results are again very similar. Table OA.6 is the counterpart to Table OA.2. The results are also very similar.

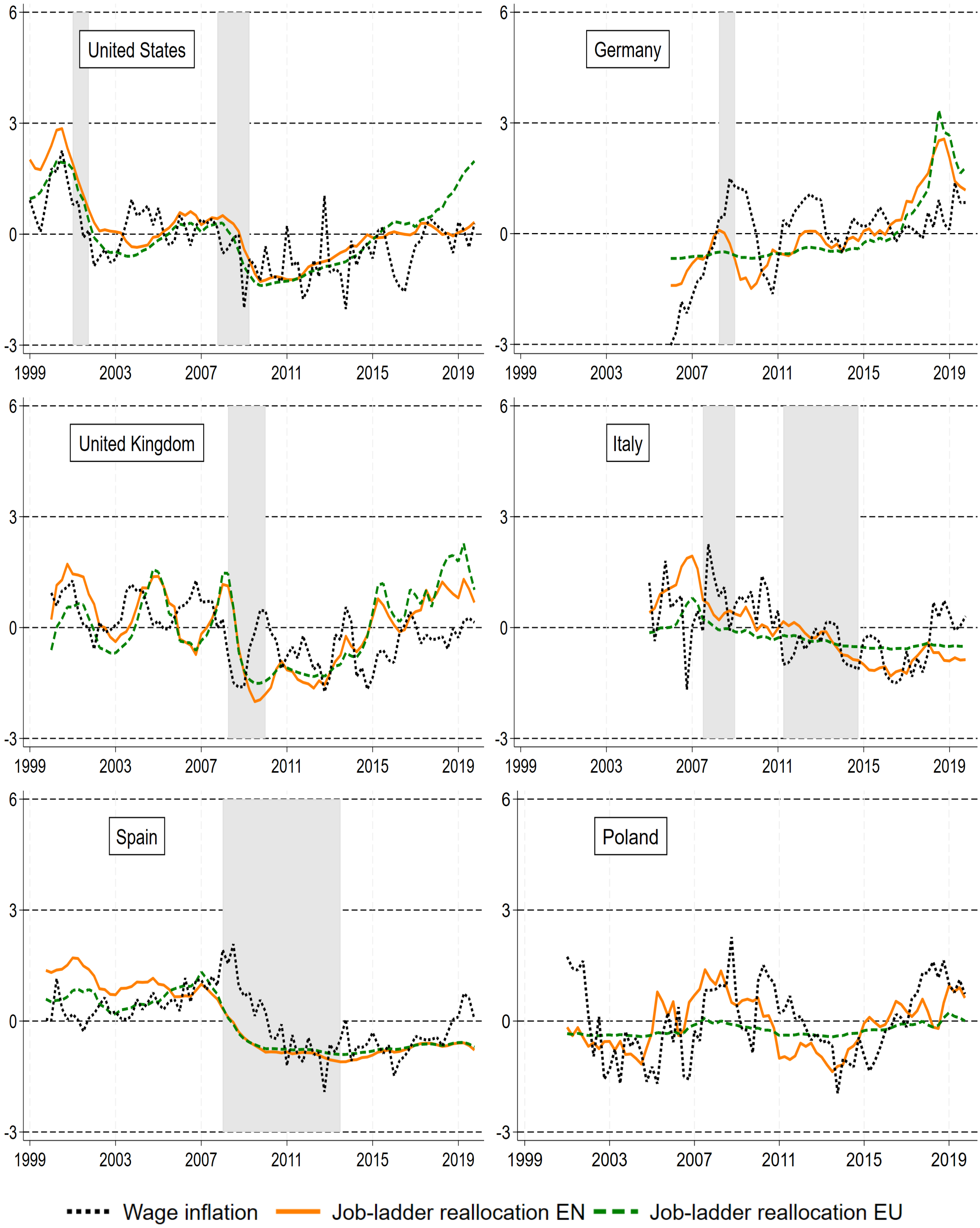

Figure OA.8: Wage inflation and the job-ladder reallocation index

Notes: Dotted line: quarterly wage inflation smoothed by a four-quarter trailing moving average. Solid line: job-ladder reallocation index ($\kappa^e = \lambda^e/\sigma$) based on p^{EN}. Dashed line: job-ladder reallocation index ($\kappa^e = \lambda^e/\sigma$) based on p^{EU}. The job-ladder reallocation index is computed as the quarter average of the monthly series smoothed by a 12-month trailing moving average. All series are normalized for comparability. Author's calculations based on data from the EULFS, the CPS, Fujita et al. (2024), Eurostat's Quarterly National Accounts and the US Bureau of Labor Statistics.

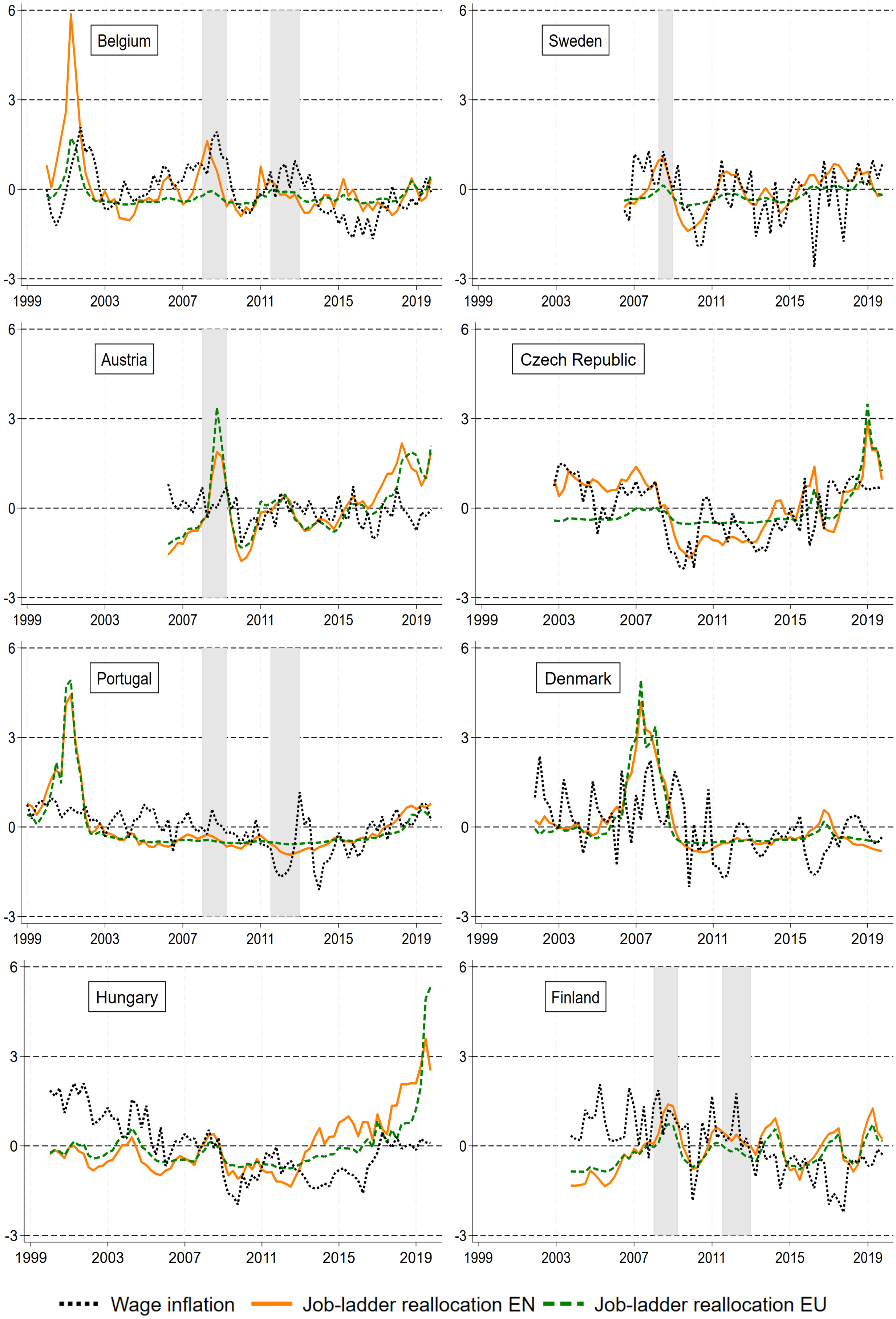

Figure 8 (Cont.): Wage inflation and job-ladder reallocation index

Table OA.4: Cyclicality and comovement of job-offer arrival rate of employed estimated using the transition rate from employment to unemployment

	(λ^e, ur)	(λ^e, p^{UE})	(λ^e, p^{EU})
United States	-0.89	0.68	-0.93
Germany	-0.48	0.05	-0.82
United Kingdom	-0.76	0.73	-0.67
Italy	-0.52	-0.13	-0.82
Spain	-0.74	0.73	-0.77
Poland	-0.52	0.50	-0.65
Belgium	-0.55	-0.03	-0.71
Sweden	-0.63	0.26	-0.82
Austria	-0.66	0.14	-0.88
Czechia	-0.54	0.55	-0.85
Portugal	-0.46	0.46	-0.55
Denmark	-0.66	0.34	-0.86
Hungary	-0.65	0.29	-0.75
Finland	-0.61	0.17	-0.86

Notes: The reported contemporaneous correlation coefficients use quarter averages of the monthly series detrended by an HP filter with smoothing parameter equal to 10^5. ur denotes the unemployment rate. Author's calculations based on EULFS, Fujita et al. (2024), and CPS data from 1998:1 – 2020:4 (starting and end dates differ across countries), working-age sample.

Table OA.5: Wage Phillips curve correlations using the transition rate from employment to unemployment

	L0		L1		L2	
	(1)	(2)	(3)	(4)	(5)	(6)
United States	0.55	0.52	0.54	0.51	0.51	0.48
	0.00	0.00	0.00	0.00	0.00	0.00
Germany	0.30	0.09	0.29	0.10	0.27	0.12
	0.06	0.29	0.04	0.25	0.02	0.17
United Kingdom	0.14	0.13	0.08	0.05	0.03	0.00
	0.15	0.19	0.48	0.64	0.82	1.00
Italy	1.05	0.78	1.16	0.99	1.45	1.44
	0.08	0.32	0.03	0.20	0.00	0.05
Spain	0.70	0.45	0.75	0.77	0.81	1.08
	0.00	0.07	0.00	0.00	0.00	0.00
Poland	3.13	3.15	3.77	3.68	4.14	4.07
	0.00	0.00	0.00	0.00	0.00	0.00
Belgium	0.71	0.62	1.06	0.95	1.21	1.13
	0.00	0.00	0.00	0.00	0.00	0.00
Sweden	1.16	0.66	1.07	0.44	1.26	0.60
	0.09	0.35	0.14	0.52	0.04	0.30
Austria	0.02	0.04	0.07	0.07	0.08	0.08
	0.81	0.47	0.48	0.40	0.41	0.36
Czechia	0.44	0.50	0.43	0.49	0.40	0.45
	0.01	0.02	0.01	0.01	0.01	0.02
Portugal	0.27	0.15	0.26	0.13	0.25	0.11
	0.00	0.03	0.00	0.05	0.01	0.07
Denmark	0.28	0.21	0.35	0.28	0.41	0.34
	0.00	0.00	0.00	0.00	0.00	0.00
Hungary	0.18	0.12	0.30	0.19	0.61	0.42
	0.23	0.25	0.18	0.20	0.06	0.09
Finland	-0.09	-0.48	-0.23	-0.69	-0.14	-0.49
	0.85	0.30	0.63	0.11	0.74	0.25

Notes: The table reports, for each country, the coefficients of the job-ladder reallocation index (calibrated using the transition rate from employment to unemployment), and its lags, from a wage inflation OLS regression (top row), and respective p-values calculated using Newey-West autocorrelation robust covariance for eight lags (bottom row). The even (odd) numbered columns refer to OLS regressions including a constant (a constant and lagged price inflation). The job-ladder reallocation index series are calculated by the author using data from the EULFS, Fujita et al. (2024) and the CPS, and are quarter averages of the monthly series filtered with a 12-month trailing moving-average. All variables are standardized for comparability. Coverage: Working-age sample from 1999:1 – 2019:4 (starting dates differ across countries).

Table OA.6: Wage Phillips correlations at different lags using the transition rate from employment to unemployment

	L0	L1	L2	L3	L4
United States	0.61	0.58	0.54	0.49	0.42
Germany	0.30	0.30	0.30	0.32	0.31
United Kingdom	0.19	0.11	0.04	0.07	0.17
Italy	0.38	0.42	0.53	0.61	0.62
Spain	0.64	0.69	0.74	0.77	0.80
Poland	0.49	0.60	0.64	0.68	0.74
Belgium	0.32	0.47	0.54	0.47	0.35
Sweden	0.28	0.26	0.31	0.33	0.24
Austria	0.04	0.16	0.18	0.01	-0.09
Czechia	0.33	0.32	0.28	0.28	0.28
Portugal	0.39	0.37	0.36	0.35	0.31
Denmark	0.31	0.39	0.48	0.48	0.48
Hungary	0.18	0.23	0.31	0.32	0.29
Finland	-0.04	-0.10	-0.06	-0.14	-0.17

Notes: The table reports correlation coefficients between wage inflation and the job-ladder reallocation index (calibrated using the transition rate from employment to unemployment) at different lags (where L1 stands for the first lag, etc.). The job-ladder reallocation index series are calculated by the author using data from the EULFS, Fujita et al. (2024) and the CPS, and are quarter averages of monthly series filtered with a 12-month trailing moving-average. Wage inflation time series are taken from the US Bureau of Labor Statistics and Eurostat, and are expressed as first-differences of the logged seasonally-adjusted compensation per hour index measured at quarterly frequency, and subsequently smoothed by a four-quarter trailing moving average. Coverage: Working-age sample from 1999:1 – 2019:4 (starting dates differ across countries).