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Measuring Labour Market Slack in Portugal: An Outcome-based Approach

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Abstract

This paper provides a comprehensive study of the heterogeneity in the Portuguese labour market. We use rich Labour Force Survey (LFS) microdata covering a complete business cycle, from 1998:1 to 2018:1, to evaluate the labour market attachment of several labour states and assess the most suitable allocation of individuals across statuses. In addition, we evaluate the adequacy of the conventional unemployment criteria.

We apply an outcome-based categorisation of labour market status by exploiting the information on the results of the behaviour of non-employed persons. To that end, we employ multinomial and binary logit models of the determinants of transitions of workers across labour market states to test for the equivalence between non-employed groups.

Overall, we conclude that heterogeneity is an evident feature of the Portuguese labour market, both between and within the conventional non-employment states. In particular, we find that the status comprising those inactive workers which want work constitutes a distinct state in the labour market and displays a transition behaviour closer to unemployment than to the group of inactive workers which do not want work. Moreover, the classification as inactive workers of individuals which report "waiting" as a reason for not having searched for a job, those individuals who have searched for a job but are still considered to be out-of-the-labour-force, as well as those individuals which are due to start work in more than three months might not be reasonable, since they show considerable attachment to the labour market and we reject the pooling of such states with their counterparts.

Keywords: labour market dynamics, heterogeneity, labour force survey, unemployment, labour market slack.

JEL codes: C82, E24, J20.

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Resumo

O presente artigo fornece um estudo extensivo da heterogeneidade no mercado de trabalho português. Utilizam-se microdados referentes ao Inquérito ao Emprego cobrindo um ciclo económico completo, desde 1998:1 a 2018:1, para avaliar a ligação ao mercado de trabalho de vários estados de trabalho e analisam-se as alocações mais apropriadas de indivíduos entre estados. Simultaneamente, avalia-se a adequação dos critérios de classificação de desemprego convencionais.

É adoptada uma classificação de estados de mercado de trabalho com base na evidência das transições entre estados, através da análise da informação referente aos resultados dos comportamentos dos indivíduos em não-emprego. Para o efeito, aplicam-se modelos multinomiais e binários logit para os determinantes das transições de indivíduos entre estados do mercado de trabalho, com vista a testar a equivalência entre grupos de não-emprego.

Conclui-se que o mercado de trabalho português é caracterizado pela existência de considerável heterogeneidade, tanto entre como dentro dos convencionais estados de não-emprego. Em particular, a evidência aponta para que o grupo de indivíduos em inactividade que expressam desejo em trabalhar constitui um estado distinto no mercado de trabalho, exibindo um comportamento de transição mais próximo do desemprego do que do grupo de indivíduos em inactividade que não expressa desejo em trabalhar. Os resultados também indicam que a classificação enquanto inactivos de indivíduos que pretendem emprego mas que não procuram por razões de espera, os indivíduos em inactividade que procuram trabalho e os indivíduos que têm um emprego para iniciar daí a mais de três meses pode não ser a mais adequada, considerando que estes exibem substancial ligação ao mercado de trabalho e se rejeita a sua equivalência para com os seus pares.

Palavras-chave: dinâmica do mercado de trabalho, heterogeneidade, inquérito ao emprego, desemprego, subutilização no mercado de trabalho.

Códigos JEL: C82, E24, J20.

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1. Introduction

The recovery from the global financial crisis and the European sovereign debt crisis that followed is mostly complete. At 2.7% per year in 2017, the Portuguese economy is experiencing the strongest growth of real Gross Domestic Product (GDP) of the past 17 years. Likewise, conventional indicators point towards an ever improving and tightening labour market. The employment ratio has increased steadily since the first quarter of 2013 and the unemployment rate is back to pre-crisis levels. Job vacancies have also increased substantially over the post-crisis period as the labour market tightens.

However, in spite of the aforementioned signs of recovery and improving labour market conditions, wage growth remains weak in most advanced countries (OECD (2018)). Portugal has not been an exception. Indeed, whereas the unemployment rate has followed a decreasing path for several years, wage growth remains exceptionally lower than it was before the global financial crisis for equivalent levels of unemployment. This background of low and decreasing unemployment and relatively stable wage inflation has frequently been regarded as a "puzzle" requiring clarification. In particular, it has prompted doubts on the ability of the unemployment rate to accurately capture the slack contained in the labour market (see, *e.g.* Yellen (2014)).

The definition of unemployment applied in the Labour Force Survey (LFS) only considers individuals without work during the reference week, who have actively searched for a job in the past four weeks, and are available to work in the next two weeks following the interview, as well as those individuals out of work, who have found a job due to start in the next three months. According to the Portuguese LFS, about four million of the working-age population were not in paid work in 2017. From these people, only about 1 in 10 satisfied the requirements to be classified as unemployed, with the remaining classified as inactive (thus deemed to be out of the labour force).

The non-employed population appears to be very heterogeneous. While the distinction between the employed and the non-employed is quite straightforward, the

boundary between the unemployed and the inactive (and therefore the associated definition of unemployment) is difficult to trace. Some persons classified as inactive can be considered close to unemployment if they have recently searched for a job or if they express desire to work. Other inactive persons do not seem to show any sort of attachment to the labour force and display little marketable skills or desire to work. Most of these groups are less likely to find a job compared to those who have recently become unemployed, but the examination of longitudinal data on worker flows appears to suggest that some subgroups within inactivity are at least as likely to become employed as the unemployed. Moreover, although the chance of transitioning from inactivity to employment is on average lower than it is from unemployment, the comparatively large size of the inactive population implies that these transitions can contribute substantially to the growth in employment, especially when unemployment decreases during expansions. One implication is that any effort towards measuring the slack in the labour market by dichotomising the non-employed into "unemployment" and "inactivity" should be expected to be unable to comprehensively capture the complexity of labour market activity.

These measurement matters are crucial for several reasons. First, since substantial attention is paid even to small variations in the headline unemployment rate and to differences in the rates across countries, measurement is of paramount importance for such analyses. Second, much economic investigation focuses on the durations in several non-employment statuses, and therefore the measurement of these spells (especially when they concern multiple categorisation changes within a single spell in non-employment) is central to this research (see, *e.g.* Clark & Summers (1979)). Third, macroeconomic fluctuations in the labour market depend on withdrawal from the labour force and cyclical participation, and these changes in turn stem crucially from persons on the margin of the current categorisations (see, *e.g.* Barnichon & Figura (2015)). Lastly, the assessment of these measurement issues may also inform theoretical research on the labour market. In particular, flow-based macroeconomic analyses of the labour market frequently apply the notion of productive "waiting" for new job opportunities, which replaces the usual notion of active search for work

(Hall (1983) and Blanchard & Diamond (1992)). Furthermore, the random matching of workers and job vacancies is often replaced by the so-called "stock-flow" matching (see, *e.g.* Coles & Smith (1994) and Coles & Petrongolo (2008)). Thus, it is apparent that many unemployment modelling studies do not fit well with the conventional measurement system which essentially relies on the job search criterion.

Against this backdrop, the aim of this paper is primarily to assess the above-mentioned issues by conducting a comprehensive study of the heterogeneity in the Portuguese labour market, covering a complete business cycle, and using rich LFS microdata from 1998:1 to 2018:1. At the same time, we evaluate the adequacy of the criteria used for the measurement of unemployment. We apply an outcome-based categorisation of labour market status by exploiting the information on the results of the behaviour of non-employed individuals. Therefore, we classify individuals into the same status if they exhibit equivalent behaviour regarding subsequent status. We consider that such an approach is a valuable complement to the conventional categorisation procedures which are essentially based upon reported information and *a priori* reasoning (*e.g.* regarding which actions should be considered to provide evidence of attachment to the labour market).

This paper is organised as follows. Chapter 2 develops our motivation, presents relevant theoretical perspectives with labour market slack measurement implications, and provides a literature review about past evidence on the heterogeneities in the labour market. Chapter 3 briefly describes the data used in our study and the adopted labour market classification strategy. Chapter 4 provides a comprehensive empirical assessment of the heterogeneity in the Portuguese labour market: we set out the statistical framework; we present an unconditional assessment; and we report the conditional assessment, including the econometric model, the discussion of the results, and a robustness check. Chapter 5 concludes.

2. The Measurement of Labour Market Slack

2.1 How good is the unemployment rate as a measure of labour market slack?

The concept of labour market slack can be defined in several ways. For the purpose of this paper, labour market slack is defined as the shortfall between the amount of work supplied by workers and the actual amount of work demanded by employers. It represents the unmet supply of paid work in an economy.

The unemployment rate is the most commonly used proxy of labour market slack. It is defined as the ratio between the number of unemployed individuals over the labour force.

Labour force surveys constitute the main source of data for the estimation of the number of unemployed individuals and their characterisation. Labour statistics split the working-age population into three mutually-exclusive groups: the employed, the unemployed, and the inactive (*i.e.* the group of individuals deemed to be out of the labour force).

However, while the distinction between the employed and the non-employed is quite straightforward, the boundary between the unemployed and the inactive (and therefore the associated definition of unemployment) is difficult to trace.

According to the Portuguese Labour Force Survey (LFS), which follows the general guidelines set by the International Labour Organisation (ILO) and the Eurostat, an unemployed person must fulfil simultaneously three conditions: (*i*) did not work during the reference week, (*ii*) is available to work during the reference week or within the next two weeks, and (*iii*) has actively searched for work during the reference week or within the previous three weeks (or, having not searched, must be due to start work in the next three months).

The classification relies on the degree of attachment to the labour market, based on the job search criterion. However, such a requirement does not necessarily square well with an economic analysis framework. The search criterion is usually not defined with respect to time or pecuniary inputs and, importantly, it does not refer to the

characteristics of the job, *e.g.* the offered wage, that could lead it to be acceptable or not. Absent is some notion of whether a specific type of search is suitable for the individual concerned, which may lead the distinction between the unemployed and the inactive to rely on survey answers containing little or no behavioural substance[1].

In addition, the non-employed population seems to be a very heterogeneous group. Some persons classified as inactive can be considered close to unemployment if they have recently searched for a job, if they express desire to work, or if they are about to start a new job but beyond the three-month threshold for an individual to be classified as unemployed. Other inactive persons do not appear to show any sort of attachment to the labour force and display little marketable skills or desire to work. A group classified as inactive which has been the subject of increasing policy concern comprises the so-called discouraged workers, which are those individuals that want to work, but do not actively search for a job. Among the reasons for not actively searching for work is the belief that no work is available. More generally, inactivity includes individuals marginally-attached to the labour force, comprising those individuals that express a desire to work, but do not engage in active search for several reasons. There has been significant debate on the criteria used to measure unemployment[2] and, in particular, on the issue of whether this marginally-attached group should be treated as inactive as is current practice.[3]

Even within unemployment the behaviour of the long-term unemployed suggests considerable variations in employability. Indeed, recent *resumé* audit investigations conclude that short-term and long-term unemployed exhibit substantial differences in the transition behaviour to employment (see Kroft et al. (2012) and Eriksson & Rooth (2014)).

Unemployment will not be an ideal metric of labour market slack if the require-

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[1]A discussion on this issue is provided in Lucas & Rapping (1969).

[2]This debate is reflected in differences in the criteria that persist between countries, as well as within countries over time (Sorrentino (2000)). Notably, many countries have switched from a concept of unemployment defined in a *broad sense* (whereby the active search criterion was not considered) to a concept of unemployment defined in a *strict sense*. For instance, in Portugal the former concept of unemployment was adopted in the survey until 1982.

[3]See Cain (1980), OECD (1987), Norwood (1988), Jones & Riddell (1999, 2006) for examples on this discussion.

ments do not sort individuals appropriately relative to their willingness to work and/or their likeliness of finding a job, *e.g.* if considerable fractions of the non-employed, which do not satisfy the requirements to be classified as unemployed, are likely to answer in a similar way when finding a relevant job vacancy.

In practice, many non-employed persons become employed without ever being recorded in unemployment. Figure 2.1 summarises the average quarterly employment inflows disaggregated by several subgroups, over the period from 2012:1 to 2018:1. We observe that indeed employment inflows originating from inactivity are substantial, and represent on average 112,000 individuals which transition into employment each quarter. This figure compares with an average of 98,000 individuals originating from unemployment, over the period under consideration. In particular, we observe that the transition pattern differs considerably between the inactivity subgroups. Approximately 11% of the marginally-attached (those that express a desire to work) move into employment each quarter on average. On the other hand, the non-attached workers are less likely to transition to employment (only 5% do so each quarter). Still, given the considerable size of the non-attached, such a low transition rate translates into non-negligible gross flows into employment in absolute terms (80,000 non-attached individuals move to employment quarterly). In addition, differences among the unemployed are also noteworthy. As expected, the short-term unemployed are much more likely to move into employment than the long-term unemployed (26.8% *versus* 16.5%, respectively).

These apparent differences in employability are reflected in the wages earned once these individuals become employed. Remarkably, inactive individuals which express a desire to work report a median net wage which is comparable to that of the unemployed (500 Euros *versus* 505 Euros, respectively), and equal to the one reported by the long-term unemployed (see the second line in table B1 in Appendix B). On the other hand, the reported net wage by those that do not express a desire to work is considerably lower (485 Euros), which is a further indication of the apparent heterogeneity among inactivity. Even though the reported median net wages by the subgroups under consideration reflect similar effects by education, by age cohort, by

Figure 2.1: Average quarterly worker flows into employment by subgroups, 2012:1-2018:1.
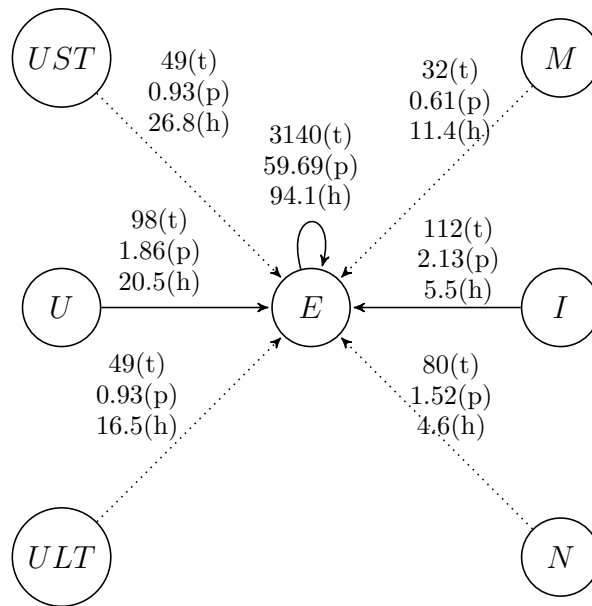
Source: Author's calculations based on the LFS.

Note: the worker gross flows are expressed as total number of individuals in thousands (t), as a percentage of the labour force (p), and as a hazard rate (h). The statistics are the quarterly averages of the period from 2012:1 to 2018:1. U, UST, ULT, I, M, and N stand for unemployment, short-term unemployment (less than 12 months), long-term unemployment (12 or more months), inactivity, marginally-attached, and non-attached, respectively.

gender, and by time out-of-employment, in level they appear to mirror substantial differences in employability, as suspected by a preliminary analysis of the transition rates.

The aforementioned subgroups of inactivity are quantitatively relevant and could thus affect one's perspective on the amount of underutilised labour supply in the market. In our data, the marginally-attached represent roughly 6% of the non-employed population and discouraged workers almost 2% (see table B2 in Appendix B). Whereas most individuals in these groups have a lower chance of moving to employment compared with the recently unemployed, they often obtain work. Therefore, they can serve to enlarge the pool of unemployed as a potential source of workers.

In sum, the unemployment rate does not capture all relevant forms of labour market slack. Particularly, measured unemployment does not account for slack that might persist within inactivity. Its chief defect is that it relies on a single-boundary conceptual framework, excluding individuals which exhibit attachment to the labour market. Therefore, it does not recognise the substantial heterogeneity in the labour supply and it ignores non-employed individuals which often move into employment.

2.2   Theoretical perspectives

The classical labour theory is not particularly useful in terms of unemployment measurement implications considering that within this framework the amount of demanded labour by firms equals the amount of supplied labour by workers at a market-clearing wage, *i.e.* no unemployment arises. This aspect of the so-called Walrasian theory of unemployment has led to the historical understanding of unemployment as (at least partially) a result of disequilibrium phenomena. Even though such terminology has contributed to the debate surrounding the modelling of unemployment, it has not improved our comprehension of the determinants underpinning unemployment or on how one should measure it.[4]

Much economic analysis of unemployment relies on the distinction between the unemployed and the inactive, with the former often modelled as those that are engaged in optimal search activities and the latter considered to be engaged in household production. The building-block of this approach is based on the observation that the job-finding process is uncertain, requiring time as well as financial resources, which contrasts with the classical model of unemployment, where the intervening agents are assumed to be fully informed at no cost on work opportunities and potential workers (Stigler (1962)). This alternative modelling approach to unemployment is referred to as the search-theory of unemployment.[5] It seeks to

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[4]It is apparent that the assumption set by the classical equilibrium theory of a centralised market wherein labour is traded at a given price does not occur in reality. Regardless, useful economic models need not be realistic, and the Walrasian paradigm is important for the analysis of many issues pertaining to labour economics. Still, it is evident that this approach is ill-suited for studying the above-mentioned topics.

[5]See Stigler (1962), Diamond (1982*a*,*b*), Mortensen (1982), Pissarides (1985), and Mortensen &

explain unemployment within a modelling framework in which an equilibrium rate of unemployment arises as a result of the optimising behaviour of workers and firms, emphasising the frictions associated to the exchange process.

In spite of its atheoretical origins, the view of identifying unemployment with active search has established itself as standard for the measurement of labour market slack.[6] Indeed, most labour market models consider those individuals classified as unemployed to be willing to work at the prevailing market wage (and therefore located at an "interior solution" regarding the desired hours of work), whereas individuals classified as inactive are modelled as being located at a "corner solution", *i.e.* in order to enter the labour market they require a higher offered wage.[7]

On the other hand, flow-based macroeconomic analysis of the labour market frequently apply the notion of productive "waiting" for new job opportunities, which replaces the usual notion of active search for work. In fact, as argued by Hall (1983), in some circumstances, "waiting" might be a productive behaviour regarding the prospects of obtaining work. For instance, the recently unemployed individuals may consider a given stock of job opportunities over which they must search and possibly apply for. As Blanchard & Diamond (1992) put it, "waiting is a more descriptive term than searching" in flow models of the labour market in which separations are a result of job destruction. Furthermore, the random matching of workers and job vacancies is often replaced by the so-called "stock-flow" matching, whereby jobs are created via the matching of the stock or the flow of vacancies with the workers which are available to work (see, *e.g.* Coles & Smith (1994) and Coles & Petrongolo (2008)). The job flows approach assumes that the process of job finding follows an endogenous duration, which ultimately specifies the level of unemployment and wages. Such a theoretical concept is more encompassing than the conventional unemployment conceptual framework, which is chiefly based upon the active search

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Pissarides (1994) for notable contributions to this field. For an extensive survey of search-theoretic models of the labour market, see Rogerson et al. (2005).

[6] In this respect, Card (2011) provides a discussion on the evolution of the concept of unemployment and its measurement, and how it relates with the existing theoretical constructs.

[7] Some examples of research which apply a three-state model for labour market behaviour are: Burdett et al. (1984), Blau & Robins (1986), and van den Berg (1990), among others.

criterion.

Moreover, segmented labour market models such as those presented by McDonald & Solow (1985) and Bulow & Summers (1986) predict that individuals might queue for job vacancies in the primary sector, instead of accepting available job opportunities in the secondary sector. Despite the fact that this behaviour is referred to as "wait" unemployment[8] by modellers, in reality such persons would be classified as inactive in the absence of the conventional search requirement.

Overall, theoretical constructs of labour market do have conceptual implications for unemployment measurement. The conventional criteria for the measurement of unemployment essentially equates its concept with active search, which is broadly consistent with search-theoretic models of unemployment. However, it is clear that many unemployment modelling studies do not fit well with the conventional measurement system.

2.3   Literature review

The study of the heterogeneity between and within labour market states is crucial for a faithful and comprehensive characterisation of the labour market slack. The literature on transition rates from labour market states into employment with implications for the classification of individuals was started by Clark & Summers (1978). In analysing the dynamics of youth unemployment for the US, the authors claim that most of youth non-employment is not captured by the unemployment statistics, since many stop searching and withdraw from the labour force. The distinction between unemployment and inactive status for youth people might be meaningless, if we consider the wide array of non-market options accessible to youths and limitations imposed by unemployment compensation schemes on the eligibility of this group. The analysis suggests that the empirical distinction between the above-mentioned statuses for this group is considerably arbitrary and of little practical value.

More generally, Clark & Summers (1979) find that transitions between unemployment and employment in the US are considerably lower in magnitude compared

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[8]Often also called "transitional" unemployment.

with transitions into and out of inactivity. In addition, many individuals appear to experience several changes in classification within a single non-employment spell, with repeated spells of unemployment discontinued by withdrawal from the labour force. Such evidence is supportive of a weak distinction between the unemployment and the inactive categories. These findings inspired several statistical analyses of the equivalence of the unemployment and inactivity categories.

Flinn & Heckman (1983) test the observation done by Clark & Summers (1978, 1979). Their work is the basis of the subsequent research on this topic. The authors rationalised the distinction between labour market states based on transition probabilities. In this sense, individuals are said to belong to the same labour market state if they exhibit equivalent behaviour with respect to subsequent labour market status.[9] The authors proposed a statistical framework for testing the behavioural equivalence of labour market states in longitudinal data, based on a duration of status econometric approach[10]. Using the National Longitudinal Survey of Young Men (NLSYM)[11], they test for the equivalence between the unemployment and inactive states for young white American males from the moment they graduate from highschool. They find evidence that rejects this hypothesis. These results are generally in agreement with versions of search theory, whereby unemployment is a state facilitating job search.

Tano (1991) employs the same line of thought, by testing the hypothesis that unemployment and inactive are behaviourally meaningless classifications using the Current Population Survey (CPS) gross flows data. To do so, the author employs a binary logit econometric framework. The results indicate that the two states are distinct for youth, whereas for prime-age individuals they are meaningless. In the same vein, Gönül (1992) extends the former analysis to a wider group of male

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[9]Therefore, two groups may be considered equally attached to the labour market if they are equally likely to move to employment in the following period.

[10]In particular, they adopt an exponential functional form in order to model the hazard rates across several labour market statuses.

[11]The NLSYM dataset is hampered by the fact that only the duration spells of non-employment and the proportion of the spell spent searching for a job are reported. Flinn & Heckman (1983) tackle this issue by excluding from their analysis all the spells of non-employment spent partly in unemployment. Still, such a procedure means that a considerable amount of data is lost and questions the findings' generalizability.

and female highschool graduates, by employing a duration econometric model, with mixed results by gender.[12] It is worth pointing out that, in the datasets used by Tano (1991) and Gönül (1992) only the employment, unemployment, and inactive states are observed, which means that they are unable to test for labour market heterogeneity within such states.

Jones & Riddell (1999, 2006) build on the former literature by examining the transition behaviour within the unemployed and the inactive groups for Canada. The authors based their research on labour market status data that enables the identification of the individuals' expressed desire to work and alternative job search strategies. They examine the equivalence between groups by applying a multinomial logit model for the transition behaviour of individuals. The authors find that the desire to work is a useful indicator for predicting employment in the subsequent period. Accordingly, the group of marginally-attached workers (comprising those inactives that do not search, but want work) is shown to be a distinct labour market state, as well as some subgroups engaged in waiting.

Brandolini et al. (2006) also find evidence of substantial heterogeneity among the inactive group for European countries. The authors investigate the role of the four-week job search requirement by examining the behaviour of those individuals who search for work but did so more than four weeks before the survey interview.[13] The authors' work is based on the European Community Household Panel (ECHP), which is a harmonised longitudinal survey coordinated by Eurostat. Their analysis is conducted by a non-parametric equality test. The results show that for most countries this group forms a distinct state in the labour market. In addition, the authors find that these individuals are behaviourally equivalent to the unemployed when their last search effort was done not long before the four-week ILO requirement, which highlights the arbitrariness of the criterion.

In the context of the Portuguese economy, Centeno & Fernandes (2004) studied the heterogeneity of its labour market. The data employed in their work is also

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[12]As opposed to Flinn & Heckman (1983), Gönül (1992) does not exclude observations from the econometric analysis, which implies allowing for multiple scenarios in a combinatorial framework, and requiring that some assumptions be put in place, *e.g.* stationary.

[13]Therefore, such workers are not eligible for unemployment.

drawn from the Portuguese LFS, for the period ranging from 1992:1 to 2003:4. The authors' methodology follows the seminal work by Flinn & Heckman (1983) in that they adopt a duration econometric framework to model hazard rates. In accordance with previous findings, the results show that the marginally-attached group is a distinct labour market state in Portugal.[14][15]

The previous works do not address the existence of heterogeneity within the unemployed state. Hornstein (2012) and Krueger et al. (2014) show that even within unemployment the behaviour of the long-term unemployed points towards considerable variations in employability. Indeed, recent *resumé* audit investigations conclude that short-term and long-term unemployed exhibit substantial differences in the transition behaviour to employment (see Kroft et al. (2012) and Eriksson & Rooth (2014)).

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[14]This finding serves as a rough guide to the present work. Even though we adopt a different econometric approach in comparison to Centeno & Fernandes (2004), as well as a longer and more recent sample period, it provides evidence that the Portuguese labour market is also characterised by heterogeneity, at least within inactivity.

[15]These findings have been confirmed by Centeno et al. (2010), with implications for the NAIRU.

3. Data Overview and Classification Strategy

3.1 The Portuguese Labour Force Survey

The Portuguese Labour Force Survey[1] (LFS) is a household survey conducted quarterly by Statistics Portugal (*Instituto Nacional de Estatística*, hereafter INE), with the goal of characterising the Portuguese labour market. The basic structure of the LFS follows the general conceptual, methodological, and precision guidelines set by Eurostat.

The LFS collects individual information on several features pertaining to the labour market, as well as demographic and socio-economic characteristics of the respondents. On the basis of this information, the INE provides quarterly estimates for the stocks of employment, unemployment, and inactivity, which in turn are used for computing several indicators, *e.g.* the unemployment rate. The richness of the data collected by the LFS allows researchers and policy-makers alike to analyse a wide range of issues related to the labour market.

Every quarter, the INE surveys approximately 40,000 individuals. The population considered in the survey is the group of residents in national territory and the sample unit is the household as main residence. The probabilistic sample of the household units is drawn via the application of a multistage stratified sampling procedure, such that each individual becomes representative of a subgroup of individuals of the population. The sampling procedure ensures an adequate precision at various levels of disaggregation, namely with respect the regions for statistical purposes (NUTS). Thus, each individual is associated with a given weight, which is then applied for conducting statistical inference to the population.[2]

The total sample is composed of six sub-samples (*i.e.* rotations) of individuals, which follow a rotation scheme whereby each quarter 1/6 of the sample is rotated out and 5/6 is kept on the sample. Thus, once selected into the LFS sample, households are interviewed for six consecutive quarters. This feature of the sample allows for

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[1] In Portuguese, *Inquérito ao Emprego.*
[2] For further details regarding the sampling procedure and the computation of the weights refer to INE (2015).

the analysis of the data in a longitudinal fashion, because five out of six rotations are the same for every two adjacent quarters. In particular, one can observe the labour force status for 5/6 of the respondents included in the sample in quarters t and $t-1$, which enables the computation of worker flows and transition rates.[3]

We had access to the LFS microdata for the period ranging from 1998:1 to 2018:1.

3.2   Algorithm for status classification[4]

The LFS data are exceptionally rich in the information supplied regarding the methods of job search, reasons for inactivity, and present activities of the non-employed, which enables to generate subgroups of non-employment potentially available to take on work. The adopted classification strategy considers several factors: (i) the findings obtained by the previous literature, which highlight the importance of an expressed desire to work by the inactive individuals as a predictor of future employment; (ii) the structure of the Portuguese LFS questionnaire; (iii) the goal of assessing the heterogeneity in the Portuguese labour market and the classification criteria followed by the INE; and (iv) sample size considerations. It results in a combined categorisation of the non-employment state into 13 mutually-exclusive and exhaustive categories. The adopted classification is summarised in figure C.1 in Appendix C.

We classify individuals in working-age into four states: employment (E), unemployment (U), marginal-attachment (M), and non-attachment (N). The employment and the unemployment states coincide with the conventional classification in the LFS. The latter two states, M and N, are obtained by disaggregating the usual inactivity state according to the wanting criterion. Assignment of the marginal attachment group relies on the LFS question "Would you like to obtain a job?". Those individuals classified by the LFS as inactive which answer "Yes" to the mentioned question are assigned to the M group. Since only those individuals that did not search for work answer the question, we also classify inactive individuals that did

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[3]In practice, we observe less than 5/6 of the sample in adjacent quarters due to non-response. See Appendix A for a discussion on this issue.

[4]The `Stata` classification algorithm used for this purpose is available upon request.

search for work into M.[5] The remainder are assigned to the N group.

Based on the LFS, we perform the conventional split of U according to duration into short- (less than twelve months) and long-term (twelve or more months) unemployed. We further disaggregate the M group into those that searched and those that did not search for work. The latter comprises four subgroups according to reasons for not searching: workers waiting for recall (which includes temporary layoffs), discouraged workers (which indicate economic reasons for not having searched[6]), workers not searching for personal reasons[7], and workers indicating other reasons for not searching[8]. Within the N group, we make a distinction between persons who have found a job due to start in more than three months (to which we refer to as long-term future job starters) and the remainder; the latter are divided into demographic groups: students, retired workers, domestic workers, disabled individuals, and other individuals.

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[5]We do so in order to ensure that the four states considered in our model are both mutually-exclusive and exhaustive.

[6]These include individuals that believe that no jobs are available, search is not worthwhile, do not know how to search, consider themselves too young/old or do not have enough education.

[7]Namely, due to sickness, looking after family, or other personal reasons.

[8]Notably, students and retired workers.

4. Heterogeneity in the Portuguese Labour Market

4.1 Statistical framework

The literature often relies on multi-state stochastic frameworks in order to analyse the dynamic features of longitudinal data. The adopted statistical framework folows the seminal contribution by Flinn & Heckman (1983) in focusing on transition rates to assess the equivalence between states and the extent of heterogeneity in the labour market.

Let Y_t be a random variable describing the status of persons in the labour market at quarter t. For the purpose of this work, Y_t is assumed discrete and takes on values corresponding to k mutually-exclusive and exhaustive states. We assume that the transition of workers among labour market states is represented by a discrete Markov chain of order 1. Therefore, the data generating process, $\{Y_t\}_{t=1}^{T}$, follows:

$$Pr(Y_t = i|Y_{t-1}, Y_{t-2}, \ldots, Y_1) = Pr(Y_t = i|Y_{t-1}) \tag{4.1}$$

wherein $i = 1, 2, \ldots, k$ indexes the observed status in the Y_t domain. The process represented by equation (4.1) is said to respect the Markov property[1]. Thus, the observed values for Y_t depend only on the current status. In other words, all other past values for the random process are irrelevant for the determination of future conditional transition probabilities.[2]

The probabilities of transition from state i to state j over time periods $t-1$ and t are given by:

$$p_{ij,t} = Pr(Y_t = j|Y_{t-1} = i), \quad i, j = 1, 2, \ldots, k \tag{4.2}$$

Consistent with the adopted status classification presented in section 3.2, we

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[1] In the analysis of labour market dynamics, such assumption is rather strict and whenever possible should be tested. This issue is addressed in section 4.3.3.

[2] In this sense, the process is said to be "memoryless".

start by considering four broad labour market states, *i.e.* $k = 4$.[3] The number of employed, E, unemployed, U, marginally-attached, M, and non-attached, N, then satisfy the following system:

$$\begin{pmatrix} E \\ U \\ M \\ N \end{pmatrix}_t = P_t \begin{pmatrix} E \\ U \\ M \\ N \end{pmatrix}_{t-1} \tag{4.3}$$

The dynamic model can be summarised by the four-by-four transition matrix P, where the ij^{th} element of the matrix, p_{ij}, represents the probability of a person moving from state $i \in \{E, U, M, N\}$ in the current period to state $j \in \{E, U, M, N\}$ in the following period:[4]

$$P_t = \begin{pmatrix} p_{EE} & p_{EU} & p_{EM} & p_{EN} \\ p_{UE} & p_{UU} & p_{UM} & p_{UN} \\ p_{ME} & p_{MU} & p_{MM} & p_{MN} \\ p_{NE} & p_{NU} & p_{NM} & p_{NN} \end{pmatrix}_t \tag{4.4}$$

In this paper, we apply an outcome-based categorisation of labour market status by exploiting the information on the results of the behaviour of non-employed individuals. Therefore, we classify individuals into the same state if they exhibit equivalent behaviour regarding subsequent status. For instance, one may consider two groups to be equally attached to the market if they are equally likely to move to employment in the next period. The approach we take generalises this idea to all the statuses considered.

Considering this Markovian framework, a necessary and sufficient condition for states M and N to be behaviourally equivalent is that the probability of moving from state M to E is equal to the probability of moving from state N to E and the

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[3]It should be noted that the flexibility of the statistical framework allows for the generalisation to any k labour states. This is important to evaluate the heterogeneity within the conventional labour states.

[4]The matrix P_t is said to be a stochastic matrix considering that $\sum_{j=1}^{k} p_{ij,t} = 1, \quad \forall i, j, t$. Consequently the transition probabilities in each row must sum up to unity.

probability of moving from state M to U is equal to that of moving from state N to U:[5]

$$\begin{cases} p_{ME} = p_{NE} \\ p_{MU} = p_{NU} \end{cases} \tag{4.5}$$

If the above condition holds, it is reasonable to pool the M and N states into a single inactivity state, *i.e.* our four-state model of the labour market collapses into the conventional model (E, U, and I). With regards to equation (4.5), the wanting-a-job criterion would not convey any useful information on labour market status of individuals.

The opposite scenario occurs if information provided by the job search question does not convey information on the labour market status. In other words, the M and U groups are behaviourally equivalent. Such a result would support the view that the traditional job search requirement for unemployment classification is too strict. The necessary and sufficient conditions for this case to hold are:

$$\begin{cases} p_{ME} = p_{UE} \\ p_{MN} = p_{UN} \end{cases} \tag{4.6}$$

If M is found to be behaviourally distinct from both the U and N states, *i.e.* if conditions (4.5) and (4.6) do not hold simultaneously, we might expect that the attachment pattern between the states follows some kind of order, for example:

$$p_{UE} > p_{ME} > p_{NE} \tag{4.7}$$

From the point-of-view of the LFS data collection methodology, such a finding would suggest the inclusion of the wanting-a-job question as a criterion for status classification.

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[5]Note that the equivalence conditions relate only exit rates into states other than the origin states under consideration.

4.2   Unconditional assessment

In this section, we study the heterogeneity in the Portuguese labour market by analysing the features of the estimated transition rates from the empirical matrix (4.4). The algorithm constructed for the estimation of the transition rates utilises the rotation scheme of the LFS, which allows to match individual's responses in one quarter to their labour market outcomes in the subsequent quarter. The algorithm is described in detail in Appendix A.

Table I shows the estimated transition rates for adjacent quarters averaged across the sample period. For transitions into E, there is a noticeable difference between U and M as origin states, with the transition rate from U at 19%, 6 percentage points above that of M (roughly 13%). Moreover, there is a striking difference between the M and N origin groups, with the transition rate from N to E averaging only 2.6%. The standard errors of the estimated transition probabilities are small (considering the LFS large sample size), such that equality of the means would be easily rejected by a formal statistical test.

Table I: Average quarterly transition rates, 1998:1-2018:1.

To ──── From	E	U	M	N
E	.967	.014	.005	.014
	(.002)	(.001)	(.000)	(.001)
U	.190	.637	.087	.085
	(.004)	(.007)	(.003)	(.004)
M	.133	.234	.370	.264
	(.003)	(.004)	(.004)	(.005)
N	.026	.015	.024	.935
	(.002)	(.000)	(.003)	(.004)

Source: Author's calculations based on the LFS.
Note:

1. Standard errors in parentheses;

2. The observations from 2010 through 2011 are not considered in the sample to avoid biases resulting from the methodological break of the LFS.

Moreover, for each non-employment destination state, the transition rates between origin groups U and M and between M and N differ considerably. For transitions into U, the average transition rate from the M group is 23.4%, which is much higher than the estimated transition rate $\hat{p}_{NU}$ (at only 1.5%); whereas for transitions into N, the $\hat{p}_{MN}$ averages approximately 26.4% in comparison to 8.5% for $\hat{p}_{UN}$.

It is worth pointing out that, judging from the results obtained for the empirical transition matrix, a person who wants to work appears to behave differently from one that does not want to work. First, someone who expresses a desire to work (M) is likely to enter the labour force in the next quarter ($\hat{p}_{MU} + \hat{p}_{ME} = 0.37$). Equivalently, a person who wants to work can be considered at the margin of participation. In contrast, a person who does not want to work (N) is very unlikely to enter the labour force in the next quarter ($\hat{p}_{NU} + \hat{p}_{NE} = 0.04$) and is therefore quite far from labour force activity and the margin of participation. Second, a marginally-attached non-participant has a higher chance of entering the labour force via unemployment than via employment (*i.e.* $\hat{p}_{MU} > \hat{p}_{ME}$), but the opposite occurs for a non-attached person, since it is much more likely to move into the labour force via employment (*i.e.* $\hat{p}_{NE} > \hat{p}_{NU}$).

The diagonal elements ($\hat{p}_{UU}$, $\hat{p}_{MM}$, and $\hat{p}_{NN}$) are numerically substantial and their analysis suggests that M is the least stable group over time, with an estimated 37% probability of an individual remaining in M from one quarter to the next, while N appears to be an absorbing group: at a retention rate of almost 94%, it is by far the most stable.

The examination of the time-series of the transition rates over the sample period (see figures C.2 in Appendix C) confirms to a large extent the behaviour observed for the average transitions obtained for the empirical matrix. Several features should be mentioned. First, the transition rates exhibit in general considerable stability over time, with the exception of the transitions into employment, for which the cyclical pattern is very marked. Second, the ordering of the transition rates is the same in *every* single quarter over the sample period, with $\hat{p}_{UE} > \hat{p}_{ME} > \hat{p}_{NE}$,

$\hat{p}_{UU} > \hat{p}_{MU} > \hat{p}_{NU}$, and $\hat{p}_{NN} > \hat{p}_{MN} > \hat{p}_{UN}$. Moreover, the difference between $\hat{p}_{UE}$ and $\hat{p}_{ME}$ is consistently much lower than the difference between $\hat{p}_{ME}$ and $\hat{p}_{NE}$. The fact that $\hat{p}_{ME}$ is close to $\hat{p}_{UE}$ is an indication that an expressed desire to work among non-participants conveys substantial information about their attachment to the labour market.

For robustness, we also examine the effect of horizon lengthening on the average transition rates.[6] The results are reported in table B3 in Appendix B. We find that, at each time interval between destination and origin quarters, the above-mentioned transition regularities are maintained. All the transition rates into E increase at longer time spans, but the ordering $\hat{p}_{UE} > \hat{p}_{ME} > \hat{p}_{NE}$ is consistent throughout. In general, the standard errors increase as the respective sample size decreases, but the differences are still statistically significant even at 4-quarter horizons.

The other elements of the empirical transition matrix also exhibit coherent behaviour as we increase the time span. The diagonal elements ($\hat{p}_{UU}$, $\hat{p}_{MM}$, and $\hat{p}_{NN}$) decrease at longer horizons, since mobility increases over time, although the impact is more noticeable for the U and the M rates. One can also observe that the hazard from U to inactivity increases slightly as we move to longer horizons. Importantly, the ordering of the estimated transition probabilities clearly holds, which further confirms the above results.

In order to examine the extent of heterogeneity within the labour market states considered, we also compute the average transition rates by detailed origin state (see table B4 in Appendix B). We perform the conventional split of U by duration into short-term and long-term unemployed. As expected, the short-term unemployed are almost twice as likely to move into E (25%) relative to the long-term unemployed (14%). Conversely, the long-term unemployed have a higher chance to remain unemployed or to transition to inactivity in the following quarter.

Furthermore, we find important heterogeneity within the M group. The striking result is that the "waiting" subgroup, which averages 23.33 thousand individuals quarterly over the sample period (approximately 12% of the M) - see table B2 in

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[6]This is done by matching individuals over longer time intervals. For example, by matching an individual in a given quarter to the same individual two quarters ahead.

Appendix B - shows a transition rate into E considerably higher than the other subgroups of M. This category displays an average hazard of 28.8% (see table B4), exhibiting quarterly rates in excess of 50% (see figure C.3 in Appendix C), as opposed to the other four subgroups that average in the range from 9% to 16%. As reported in table B4, the higher hazard into E coexists with a much lower hazard into N, *i.e.* the waiting subgroup is not only more likely to transition into E, but also less likely to become non-attached. Moreover, those M individuals which report having searched for a job, which amount to roughly 14 thousand individuals quarterly on average (corresponding to 7% of the M), also display significant attachment to the labour market. In particular, approximately 16% of these individuals move to employment quarterly on average, which is above the transition rate of the long-term unemployed (14%). Despite this, such individuals also move often to N (19% do so each quarter on average), which is still considerably below the corresponding transition rate displayed by most of their M counterparts.

A further set of measurement issues we aim at addressing arise for persons which do not search for work but have found a job due to start in more than three months (or within three months, but do not meet the availability criterion), to which we refer to as long-term future job starts. In Portugal, as in many other countries, such persons are classified as inactive. Therefore, statistical agencies treat this subgroup in a different way relative to those that have found a job due to start within three months and are available (which do not need to fulfil the job search criterion to be categorised as U). This subgroup of N amounts to 1.44 thousand individuals quarterly on average over the sample period in consideration (see table B2 in Appendix B). The last panel of table B4 presents the hazards for this group, as well as for the remainder of the non-attached group. We find that long-term future job starts display the largest hazard into E of all subgroups considered: approximately 39% move into employment on average every quarter. However, they also exhibit an almost as high hazard into inactivity, which makes it hard to evaluate this classification practice based on these unconditional data. Still, it is apparent that long-term future starts display very different transition behaviour in comparison

with other non-attached workers.

In sum, these unconditional data suggest that the U, M, and N groups exhibit considerably distinct behaviour. It appears that the behaviour of the M is closer to that of the U than to the N, but the U and the M groups may nevertheless be distinct labour market states.[7] The differences are quantitatively large and consistent with previous evidence found by Jones & Riddell (1999) for Canada. Accordingly, we find that searching for a job and an expressed desire to work among non-participants conveys substantial information about a person's attachment to the labour market.

We also find substantial heterogeneity within labour market states. In particular, the short-term and the long-term unemployed display substantially different transition behaviour. Moreover, the waiting subgroup of M shows stronger attachment relative to the remainder that express desire to work. In fact, on the basis of the empirical transition rates to employment, the waiting subgroup of M is more attached than the unemployed. Those individuals classified as inactive, but who have nevertheless searched for a job, also appear to be more attached to the labour market than their M counterparts, exhibiting transition rates into E in excess of the long-term U. Likewise, the long-term future job starts appear to be much more attached to the labour market than their non-attached counterparts.

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[7]Such a conclusion would support the view that M is an intermediate state, lying in between U and N.

4.3   Conditional assessment

The findings obtained for the unconditional transition rates are informative, but must be treated with caution. The average transition rates analysed consider persons who differ on various characteristics. Therefore, it is crucial to assess whether the findings are essentially due to compositional effects, such that different types of persons are more or less likely to belong to different groups than others, with an impact on the respective transitions, or whether the findings still hold after controlling for such differences. A conditional assessment is thus called for. In this section, we specify the econometric apparatus used for this assessment. We then present and discuss the results. Finally, we address several limitations of the adopted specification by performing a robustness check.

4.3.1   Econometric model

We estimate multinomial logit models (MLM)[8] of the determinants of transitions across several employment and non-employment states.[9] Such models will enable us to test whether two origin states are equivalent controlling for the observable characteristics of the individuals. This amounts to testing the conditional versions of the restrictions (4.5) and (4.6) presented above.

The choice of modelling transition rates through MLM, as opposed to alternative longitudinal frameworks is due to two reasons. The first reason is related with the potential issue of attrition. A longitudinal framework is more associated with persistence and is more sensitive to attrition. However, the current analysis is more concerned with recurrence, since any transitions across time periods are under consideration despite potential problems of attrition[10]. Second, since the main focus of this work is on non-employment groups in which duration is not well measured, we consider that this econometric approach is preferable to employing a duration mod-

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[8]For an overview of the multinomial logit class of models, see Greene (2012) and Hosmer et al. (2013).

[9]As opposed to Jones & Riddell (1999), we report the results from pooled multinomial logit regressions, since it has the advantage of increasing the sample size. We have also estimated the same set of models for each of the transitions quarterly, with very similar results.

[10]In other words, we are analysing an unbalanced panel.

elling framework (as have done, *e.g.* Flinn & Heckman (1983) and Gönül (1992)), because we refrain from additional assumptions regarding the functional form of the model.

The individual conditional transition probabilities are as follows:

$$p_{ij,h,t} = Pr(Y_{h,t} = j | Y_{h,t-1} = i, \boldsymbol{x}_{h,t}), \quad h = 1, 2, \ldots, n \tag{4.8}$$

where h indexes the person, $Y_{h,t}$ denotes the first-order Markov chain for person h at time t, and $\boldsymbol{x}_{h,t}$ refers to any vector of conditioning individual characteristics. The labour market states are constructed such that they are both mutually-exclusive and exhaustive. Therefore, the probabilities add up to unity for each individual h, *i.e.* $\sum_{j=1}^{k} p_{ij,h} = 1, \forall h$.

The simplest approach to the MLM is to define one of the outcome categories as a baseline, compute the log-odds with respect to the baseline category, and then let the log-odds be a linear function of the covariates. As such, the probability of moving into a category is compared to the probability of membership in the baseline category. Considering that, in the most general case, we have k categories, such an approach requires the computation of $k-1$ equations, one for each destination state with respect to the baseline. Thus, there will be $k - 1$ predicted log-odds. If we define the j^* as the baseline outcome, we obtain the following system:

$$f_j(\boldsymbol{x}_{h,t}) = \ln \frac{Pr(Y_{h,t} = j | Y_{h,t-1} = i, \boldsymbol{x}_{h,t})}{Pr(Y_{h,t} = j^* | Y_{h,t-1} = i, \boldsymbol{x}_{h,t})} = \alpha_j + \boldsymbol{x}_h' \boldsymbol{\beta}_j, \quad j \neq j^* \tag{4.9}$$

Where α_j denotes a constant and $\boldsymbol{\beta}_j$ denotes the vector of regression coefficients. According to the MLM, the predicted transition probabilities can be expressed as follows:

$$p_{ij,h,t} = \begin{cases} \dfrac{\exp\{f_j(\boldsymbol{x}_{h,t})\}}{\sum_{j=1}^{k} \exp\{f_j(\boldsymbol{x}_{h,t})\}}, & \text{if } j \neq j^* \\ \dfrac{1}{\sum_{j=1}^{k} \exp\{f_j(\boldsymbol{x}_{h,t})\}}, & \text{if } j = j^* \end{cases} \tag{4.10}$$

Since $f_{j^*}(\boldsymbol{x}_{h,t}) = 0$, we obtain $\exp\{f_{j^*}(\boldsymbol{x}_{h,t})\} = \exp\{0\} = 1$. In our model, we

set $j^* = i$, *i.e.* we define the baseline outcome as the individual remaining in the previous state. The model is estimated via maximum likelihood procedure.[11]

A variety of transition probability tests can be executed through tests on the comparison of coefficients. In particular, likelihood ratio tests can be implemented for some alternative imposed as a restriction on the vector of coefficients.

We aim at testing for the equivalence between the probabilities of transitions into different labour market states, for instance, to test whether one can pool individuals originating from state M with individuals originating from state N. To do so, we take all individuals in our sample which occupy the M or N state in the first period, such that their three destination outcomes are E, U, or to remain in the pooled inactivity state, and we run a multinomial logit regression, as in equation (4.9). The covariates refer to the personal and socio-economic characteristics of the respondents, as well as to a set of seasonal and regional dummy variables[12] (see table B5 in Appendix B).

Afterwards, an unrestricted model is estimated, by adding a dummy variable identifying the individuals which were originally in state M. The origin state dummy is interacted with each explanatory variable. Therefore, the unrestricted model allows for distinct intercepts and influences of the conditioning characteristics of the individuals, depending on their origin state, *i.e.* distinct transition behaviour for individuals who originate from M and N.

In order to test for the equivalence between M and N, *i.e.* condition (4.5), we employ a likelihood-ratio test, which compares the maximised values of the logarithm of the likelihood function under the null hypothesis of equivalence between groups and under the alternative hypothesis that the groups are different[13].

The same reasoning is applied to test whether there is statistical evidence supporting the equivalence between the M and the U states on the basis of their tran-

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[11]The maximum likelihood estimator, $\hat{\boldsymbol{\beta}}_j$, is consistent, asymptotically efficient, and normally distributed. See Greene (2012) for a proof.

[12]Seasonal dummy variables are added because the seasonal behaviour of the transitions is very marked, which might distort our conclusions if not appropriately accounted for.

[13]The corresponding test statistic follows a chi-squared distribution with degrees of freedom equal to the number of restrictions imposed under the null, if the null is true (Greene (2012)).

sition rates, *i.e.* to test for the condition (4.6), as well as for testing the equivalence between other subgroups of non-employment.

In practice, the adopted methodology assesses whether two origin states provide sets of coefficients which are statistically significantly equal to each other. In other words, we test whether one should pool together the two origin states, by applying a joint model for the respective transition probabilities. On the one hand, in the case that the coefficients are found to be significantly equal, such that the states can be pooled without any information loss, then we conclude that the states under consideration are equivalent. On the other hand, if the sets of coefficients are found to be statistically different at some suitable significance level (*i.e.* we reject pooling the states together), we infer that the states should be considered distinct.[14]

Since the LFS was subject to a survey redesign in the first quarter of 2011, we are forced to conduct the tests separately for each survey. The results will enable us to assess the extent of heterogeneity in the Portuguese labour market.

4.3.2   Discussion of results

The results of the above-mentioned likelihood-ratio tests for the pairwise equivalence between the U, the M, and the N groups are reported in table II. For each test, the observed value of the test-statistic and the respective $p-$value are presented. Given our interest in the equivalence tests rather than on the interpretation of the estimated MLM regressions, we relegate the corresponding MLM estimations to Appendix D.[15]

We evidently reject the equivalence between M and N, M and U, and N and U, both in the first and second LFS series. This finding can be inferred from the large values for the observed likelihood-ratio test statistic and the respective

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[14]Despite its convenience, the adoption of a multinomial logit econometric framework raises the concern over the independence between the possible transition outcomes, *e.g.* whether the relative rates of transition into employment and unemployment would change if the outcome to remain in the marginally-attached and non-attached pooled state were removed. We address this issue in subsection 4.3.3.

[15]The estimated regressions are too numerous to report here. We only report those estimations concerning the equivalence between U, M, and N. The remainder are available upon request. We highlight that the majority of the estimated coefficients are significant at the usual significance levels.

TABLE II: Multinomial logit likelihood ratio test for the equivalence between non-employment states.

	Time period	
H_0	1998:1-2010:4	2011:1-2018:1
$M = N$	9021.85 (0.000)	5587.18 (0.000)
$M = U$	2816.79 (0.000)	6586.40 (0.000)
$U = N$	121896.63 (0.000)	82709.68 (0.000)

SOURCE: Based on LFS data.
NOTE: The reported values are the observed likelihood-ratio test statistics for the respective H_0. The $p-$values are reported in parentheses.

$p-$values equal to 0.000 for all the conducted tests. Such results provide evidence supporting the hypothesis that the group comprising marginally-attached workers is distinct from the non-attached, on the basis of the full multinomial logit model, as well as rejecting the equivalence between the marginally-attached group and the unemployed. Furthermore, we decisively reject the pooling of the unemployed and the non-attached groups.[16] Hence, these formal statistical tests, which account for the observed differences of the individuals in each state, generally corroborate the evidence found for the unconditional assessment.

We also test the heterogeneity within the groups of unemployment, marginal-attachment, and non-attachment (see table B6 in Appendix B). For the unemployed, our results point towards a rejection of the equivalence between the short-term and the long-term unemployed. In addition, within the marginally-attached, the statistical evidence leads to a clear rejection of the equivalence between its subgroups. Finally, within the non-attached group, we test and strongly reject the null of equivalence between future job starts and other non-attached.[17]

Lastly, we conduct statistical tests of two equivalence hypotheses which compare subgroups across the conventional classification criteria. As depicted in figure C.3 and table B4, there is substantial heterogeneity within the marginally-attached. It

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[16]Such a hypothesis was much less plausible from the unconditional analysis.
[17]Such a finding is not at all surprising considering the markedly different empirical transition rates observed for these subgroups.

is apparent that those marginally-attached which report "waiting" ($M(W)$) as a reason for not searching exhibit higher transition rates to employment relative to the other subgroups and, importantly, relative to the unemployed. The heterogeneity within non-attachment is also noteworthy, since future job starts ($N(FJS)$) display on average transition rates to employment above the unemployed, and clearly above those of other non-attached individuals.[18] These observations provide a *prima facie* for investigating whether such non-employment states are equivalent to the unemployed. Table B7 in Appendix B reports the results.

The tests again lead us to reject equivalence between all the states considered. However, one can argue that, to the extent that the tests reject pooling the states, it is mainly due to $p_{M(W)E} > p_{UE}$ than the other way around. The same conclusion can be inferred for those future job starts classified as non-attached. Such findings might indicate that the adopted criteria for unemployment lacks empirical foundations. Particularly, the classification as inactive workers of non-employed individuals which indicate waiting and future job starts might not be reasonable.

4.3.3 Limitations and robustness check

Independence of irrelevant alternatives

We recognise that the adopted statistical framework is hampered by several drawbacks. The MLM specification implicitly imposes the independence of irrelevant alternatives assumption (IIA) (see Luce (1959)). Under this strong assumption, the relative probabilities of transitions into, *e.g.* E and U, would not change given the removal of the (irrelevant) alternative of transitions into inactivity. Such a scenario seems unrealistic considering that U is in one sense closer to inactivity than to E.

Hausman & McFadden (1984) developed a Hausman-type test of the IIA[19]. We conduct this IIA test for the multinomial logit models applied for the equivalence

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[18]As already noted, the group comprising future job starts also exhibits low probabilities of staying in non-attachment *vis-à-vis* the very high retention rate of non-attached individuals.

[19]An alternative test of the IIA has been proposed by Small & Hsiao (1985). We choose to report the Hausman-McFadden tests because the Small-Hsiao test relies on the creation of random half-samples from the data, which implies that results may differ considerably for successive calls of the test; nonetheless, both tests provide mixed results in our data.

between M and N, and M and U[20]; the results are reported in tables D5 and D6 in Appendix D, respectively. We obtain mixed results for each outcome, which depends on the category omitted from the full model. Therefore, we cannot rule out the presence of IIA in the multinomial logit models.

To assess the robustness of our results, we thus estimate binary logit models, which can be viewed as imposing the polar assumption of complete dependence.[21][22]

The statistical framework resembles the one outlined in section 4.1, only that the transition matrix now becomes:

$$P_t = \begin{pmatrix} p_{E,E} & p_{E,\overline{E}} \\ p_{\overline{E}_1,E} & p_{\overline{E}_1,\overline{E}} \\ p_{\overline{E}_2,E} & p_{\overline{E}_2,\overline{E}} \\ \vdots & \vdots \\ p_{\overline{E}_{13},E} & p_{\overline{E}_{13},\overline{E}} \end{pmatrix}_t \tag{4.12}$$

where $\overline{E}$ denotes the non-employment state and the 13 non-employment mutually-exclusive subcategories are identified from $\overline{E}_1$ to $\overline{E}_{13}$. For the sake of simplicity, the outflows from E and transitions across non-employment states are ignored.

As noted previously, we are interested in hypotheses pertaining to comparisons to the unemployment group. For instance, we aim at assessing whether the transition rate from the inactive subgroup which states "personal reasons" for not searching is

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[20]The test comprises the following stages. First, we estimate the full model with k possible outcomes and the respective estimates are included in $\widehat{\boldsymbol{\beta}}_F$. Second, we estimate a restricted model by removing one of the possible outcomes and the respective estimates are included in $\widehat{\boldsymbol{\beta}}_R$. We proceed to determine $\widehat{\boldsymbol{\beta}}_F^*$, a subset of $\widehat{\boldsymbol{\beta}}_F$ obtained by removing the coefficients which are not considered in the restricted model. The test is then based on the following test statistic:

$$Q_{IIA} = (\hat{\boldsymbol{\beta}}_R - \hat{\boldsymbol{\beta}}_F^*)'[\widehat{Var}(\hat{\boldsymbol{\beta}}_R) - \widehat{Var}(\hat{\boldsymbol{\beta}}_F^*)]^{-1}(\hat{\boldsymbol{\beta}}_R - \hat{\boldsymbol{\beta}}_F^*) \tag{4.11}$$

which follows asymptotically a chi-square distribution with degrees of freedom equal to the number of coefficients contained in $\hat{\boldsymbol{\beta}}_R$, if the null of IIA holds. A significant value for Q constitutes evidence against the IIA. Hausman & McFadden (1984) note that the test-statistic might assume negative values if $\widehat{Var}(\hat{\boldsymbol{\beta}}_R) - \widehat{Var}(\hat{\boldsymbol{\beta}}_F^*)$ is not a positive semi-definite matrix, and indicate that a negative Q is evidence supportive of the null of IIA.

[21]In fact, the MLM is an extension of the binary logit model, whereby the probability distribution is multinomial as opposed to binomial and we obtain $k-1$ equations instead of one. If $k=2$, the model collapses into the usual logistic regression model.

[22]We have performed binary logits for all outcomes. The results are in line with those presented in this section, and reinforce the robustness of the previous findings.

comparable to the one of the unemployed, *ceteris paribus.* From a practical point-of-view, it is also relevant to check whether the estimated transition rate is higher for some subgroup of inactivity relative to the unemployed.

We take advantage of this statistical framework, to conduct a more detailed assessment of the heterogeneity in the Portuguese labour market. Namely, we perform the same set of equivalence tests relative to both the short-term and the long-term unemployed. The tests' associations are summarised in table D7 in Appendix D, in order of transition rate (from the highest to the lowest).[23] The existence of any of these marks challenges the use of the unemployment rate for slack measurement purposes, even though the literature on this topic usually focuses on the hypothesis marked by "♣" (as we have addressed in the previous section).[24]

For this purpose, and in order to ensure that the assessment is as robust as possible, we estimate two binary logit models. A simpler model only controls for the seasonal and the regional pattern of the transitions rates, whilst a more complete model adds the usual demographic and socio-economic individual explanatory variables.[25]

By employing this approach to the simplest model (which only accounts for the seasonal and regional transition effects), we find that 3 of the 11 inactive subcategories considered are in some sense comparable to unemployment with respect to their attachment to the labour market (see the second column of table D8 in Appendix D). These include the inactives which have searched for a job, the marginally-attached workers which are "waiting", and long-term future job starters. The consideration of individual controls in a more complete logistic model reinforces these findings, since the tests do not change significantly (see the third column of table D8).

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[23]To keep the table of results manageable we only display the tests for the highest transition, *e.g.* if some subgroup qualifies for "★", the "♣" is not shown.

[24]The equivalence test relative to the long-term and the short-term unemployed is performed via a test for equality of the respective coefficients. However, the test for the equivalence relative to the overall unemployment status is most easily achieved through an auxiliary model whereby the short- and long-term unemployment are replaced by the usual unemployment term.

[25]The fact that the coefficient estimates on these variables are mostly statistically significant supports their consideration in the model.

This robustness assessment (based on relaxing the IIA assumption) indicates that, as initially suspected from the findings obtained for the MLM equivalence tests, several subgroups within inactivity might be better treated as equivalent to unemployment from a labour supply perspective.

Markov assumption and state dependence

In our model, we assumed a stringent Markovian statistical framework. The stationary Markov assumption, whereby transition probabilities depend solely on the current labour market status, and not on the time spent in such state, does not allow for duration dependence in U (see, *e.g.* Kroft et al. (2012) and Farber et al. (2015)) and similar persistence phenomena in E and spells in other non-employment states (Kudlyak & Lange (2014)).

We examine whether duration dependence is driving the above findings by reducing the sample to those individuals with non-employment spells of less than 12 months (*i.e.* 4 quarters)[26] and we re-fit the models to this sample.[27]

Once more, the likelihood-ratio tests performed on the multinomial logit models which (partially) account for duration dependence effects lead to an overwhelming rejection of equivalence across U, M, and N (see table B8 in Appendix B).

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[26]The decision for 12 months instead of some other shorter time threshold is motivated by sample size considerations. One should keep in mind that we therefore implicitly assume no substantial duration dependence issues provided the person has been employed over the last 12 months.

[27]Another way to address this issue would be to utilise self-reported interrupted durations in order to control for labour market states observed before the LFS observation time span, but such self-reports are not available on the Portuguese LFS.

5. Conclusion

This paper provides a comprehensive study of the heterogeneity in the Portuguese labour market using rich LFS microdata covering a complete business cycle, from 1998:1 to 2018:1. We primarily aim at evaluating the labour market attachment of several states and therefore to assess the most suitable allocation of individuals across statuses. In addition, we evaluate the adequacy of the conventional unemployment criteria.

We apply an outcome-based categorisation of labour market status by exploiting the information on the results of the behaviour of non-employed individuals. Therefore, we classify persons into the same status if they exhibit equivalent behaviour regarding subsequent status. We consider that such an approach is a valuable complement to the conventional categorisation procedures which are essentially based upon reported information and *a priori* reasoning (*e.g.* regarding which actions should be considered as providing evidence of attachment to the labour market); however, we do recognise that the evidence reported herein does not in itself settle many of such contentious matters.

The findings of this paper might prove useful to policy-makers, statistical agencies, and researchers working on several areas of labour economics in Portugal. The main findings are as follows:

- By disaggregating the non-employed population into three subgroups (the unemployed, the marginally-attached, and the non-attached), we find an evident behavioural distinction between each of these subgroups. The unemployed find work more frequently relative to the marginally-attached, who in turn move to employment in the subsequent quarter with a probability almost 10 p.p. above that of the non-attached. These differences in the transition rates into employment coexist with related transitions into the non-employed statuses under consideration, and are reflected in the reported wages of the individuals in each of these groups.

- On the basis of likelihood ratio tests of equivalence, we conclude that the marginally-attached group constitutes a distinct state in the labour market.

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We thus reject the conventional three-state model for the labour market. Moreover, marginally-attached workers display a transition behaviour closer to unemployment than to the non-attached, which accords with previous findings. Therefore, "wanting" a job is a good predictor of future employment. This result suggests that it would be convenient for statistical agencies to take into account four labour market statuses and for econometric research on transitions to consider disaggregating non-employment into a multi-state model.

- We find significant heterogeneity among the marginally-attached. In particular, the "waiting" subgroup displays a much higher transition rate into employment, as well as a lower probability of moving to non-attachment *vis-à-vis* its counterparts in marginal-attachment. Such a result implies that those individuals which express a desire to work and report "waiting for recall or responses" as reason for not searching warrant careful policy attention and their consideration in supplementary measures of labour market slack should be discussed. Indeed, by comparing this subgroup with the unemployed we find evidence supporting their classification as unemployed workers, as opposed to inactive as is current practice.[1] The performed likelihood ratio tests for the equivalence of these groups lead to rejection of their equivalence; nevertheless, we consider that this rejection is mainly driven by the fact that the "waiting" subgroup exhibits a much stronger tie to the labour force than the unemployed, than the other way around. Moreover, this finding in itself provides some adherence to theoretical constructs of the labour market which underscore wait/transitional unemployment.

- Within the marginally-attached population, we also observe that those individuals who have searched for a job but are still classified as inactive (either because they have searched passively and/or do not fulfil the other requirements for unemployment classification) display a transition rate into employ-

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[1] We have computed the unemployment rates from 2012:1 to 2018:1 by including the "waiting" subcategory of the marginally-attached. The difference relative to the usual unemployment rate is on average 0.2 p.p..

ment which is comparable to the long-term unemployed (even after controlling for individual characteristics). The formal equivalence tests also reject their equivalence to their counterparts. These results further question the validity of the current measurement practices, even though the evidence supporting the inclusion of this subgroup in unemployment is not as strong as is for the "waiting" subcategory.

- We find substantial heterogeneity among the non-attached. This is essentially due to the fact that the so-called long-term future job starters display the highest degree of attachment to the labour market, judging by its average transition rate into employment, the largest of all the subgroups under the scope of our assessment. We reject the pooling of this state with both its counterparts and unemployment, but we again argue that this is due to the fact that it displays a larger hazard into employment than the unemployed (which is corroborated by the binary logit robustness assessment). Although these individuals also frequently withdraw to other states in non-attachment, it is clear that their behaviour is nearer to unemployment than to the rest of non-participants.

- Overall, we conclude that heterogeneity is an evident feature of the Portuguese labour market, both between and within the conventional non-employment states. The econometric analysis largely corroborates the findings for the empirical transition rates, and is robust to several modelling issues. We find that the pooling of individuals into broad states is unlikely to faithfully describe labour market dynamics. From this perspective, labour market slack measures based on strict in or out criteria, *e.g.* job search, are unable to comprehensively capture the amount of underutilisation of the labour supply. Nevertheless, job search and the reported desire to work are found to be meaningful indicators.

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Appendices

A.   Algorithm for computation of transition probabilities[1]

In this section, we describe the algorithm constructed with the goal of estimating the gross worker flows and the corresponding empirical transition probabilities applied in the Markovian model of the labour market dynamics, represented by equation (4.4).

The algorithm takes advantage of the rotation scheme of the Portuguese LFS, whereby each quarter 1/6 of the sample is rotated out and 5/6 is kept on the sample. Therefore, the LFS interviewees remain in the sample for six consecutive quarters. Two techniques for the computation of the worker flows can be considered: a change in status today relative to the previous quarter (backward matching) or a change in the following quarter relative to today (forward matching). In the former case, quarters 2, 3, and 4 are matched with their respective counterparts in a backward fashion, while in the latter, quarters 1, 3, and 5 are matched with their respective counterparts looking forward. It is worth pointing out that such backward and forward matching techniques are not simple conventions, since the transition probabilities differ depending on which method we use. This is related with the fact that the sample weights are drawn from different quarters. In our study, we apply the backward matching technique, and therefore the worker flows are population-weighted sums of all individuals changing labour market status from one quarter to the next.

The matching algorithm tracks the labour market status of each individual over the six quarters they remain in the sample, according to the individual's unique identifier. Previous to the 2011 survey redesign, the matching criterion is based on a core set of variables[2], since no individual unique identifier is made available. Furthermore, at each pair of adjacent quarters, we validate the aforementioned matched transitions using two observable personal characteristics: gender and age. Those inconsistent observations are dropped from our sample, which in practice causes the

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[1]The `Stata` algorithm is available upon request.

[2]These include: the accommodation identifier, the location identifier, the household identifier within the accommodation, and the individual identifier within the household.

fraction of successful matched individuals to be less than 5/6 of the original sample.

Subsequent to the construction of the matched sample, we cross-tabulate the labour market status for each quarter, such that we obtain a matrix which reports the corresponding worker flows between the labour market states, $\hat{F}_{ij}, i, j \in \{E, U, M, N\}$. By iterating this process at each pair of adjacent quarters contained in the sample, we generate the series of worker flows. The transition rates from state i to state j are computed as the ratio of the corresponding flows over the sum of the outflows from the original state[3]:

$$\hat{p}_{ij,t} = \frac{\hat{F}_{ij,t}}{\sum_k \hat{F}_{ik,t}}, i, j, k \in \{E, U, M, N\} \tag{A.1}$$

Nonetheless, there are two main impediments to constructing a continuum of transition probabilities from 1998:1 to 2018:1. First, from 1998:4 to 1999:1, the INE scrambled the household identifiers. Second, from 2010:4 to 2011:1, the individual identifiers were changed as a consequence of the mentioned survey redesign. Consequently, we were unable to match the individuals over these quarters and compute the corresponding flows and transition probabilities. Therefore, in order to obtain a continuous series, in the first case we apply a matching procedure based on the individuals' personal characteristics[4], and in the second case, we employ an imputation method for these quarters such that we keep the seasonal pattern of the flows unchanged[5].

Lastly, we should mention briefly that the estimation of the gross worker flows and the corresponding transition probabilities relies on linked survey data and accordingly is subject to (i) missing data and (ii) classification error problems[6]. Missing data may arise due to sample attrition, *e.g.* persons moving out of the sample before being reinterviewed, which effectively means that the algorithm is unable to

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[3]We use the sum of outflows instead of the original state's stock to minimise attrition bias.

[4]We thank Lucena Vieira for providing the identification key to match individuals from 1998:4 to 1999:1.

[5]We do so via the estimation of a four-quarter moving-average procedure. See Heeringa et al. (2010) for a comprehensive presentation of survey data imputation techniques.

[6]See, *e.g.* Abowd & Zellner (1985), Poterba & Summers (1986), and Clarke & Tate (1999) for analyses on the issues regarding the estimation of worker flows and transition probabilities using survey data.

track such individuals throughout. A main concern is that such sample attrition may be correlated with the labour status of the person, which would mean that the data are missing at a non-random basis. Classification errors mean that a person's labour market status is not correctly classified. It may occur due to erroneous responses provided to survey questions (*e.g.* related to proxy respondents), misunderstandings of the interviewer, or mistakes in the data collection process. Such errors tend to offset in cross-sectional data if at random. However, in longitudinal data such errors are cumulative, because a single classification error can lead to two incorrect transitions in gross flow data. There is no practical way to deal with such classification error biases.

A fair deal of data construction problems is associated with the use of the survey and we address a few crucial issues here. Notwithstanding, we consider that the efforts reflect a fine compromise given the available data.

B. Tables

TABLE B1: Reported net wages of previously non-employed subgroups, 2011-2018.

	Unemployment	Short-term Unemployment	Long-term Unemployment	Marginally-attached	Non-attached
Total sample	505.0	530.0	500.0	500.0	485.0
by Education					
No education	450.0	485.0	350.0	400.0	180.0
Basic education	500.0	505.0	485.0	485.0	430.0
Secondary education	505.0	520.0	500.0	500.0	485.0
Higher education	600.0	676.0	580.0	600.0	680.0
by Age cohorts					
15-24	500.0	500.0	500.0	500.0	419.0
25-34	525.0	550.0	500.0	505.0	500.0
35-44	510.0	550.0	500.0	490.0	507.0
≥45	505.0	530.0	500.0	485.0	480.0
by Gender					
Male	533.0	557.0	505.0	500.0	500.0
Female	500.0	505.0	485.0	485.0	375.0
by Time out-of-employment					
<1 year	525.0	–	–	500.0	500.0
1-2 years	520.0	–	–	500.0	500.0
≥2 years	505.0	–	–	489.5	485.0

SOURCE: Author's calculations based on the LFS.
NOTES:

1. The observations from 2010 through 2011 are not considered in the sample to avoid biases resulting from the methodological break of the LFS;

2. The values are the medians of the reported net wages in Euros of each group.

TABLE B2: Summary estimates by detailed status, 1998-2018.

Status	Stocks (thousands)	Fraction of non-employment (%)	Flows into employment (thousands)	Fraction of new employment provided (%)	Hazard rates into employment (%)
Unemployed	472.07	14.67	65.50	48.15	18.98
Short-term unemployed	213.85	6.70	38.24	29.64	24.61
Long-term unemployed	258.01	7.96	27.23	18.49	13.70
Marginally-attached (want)	199.69	6.16	18.35	12.65	13.12
Inactive searcher	13.99	0.43	1.54	1.05	16.07
Waiting	23.33	0.76	4.48	4.03	29.46
Discouraged	54.80	1.69	4.06	2.59	9.23
Personal reasons	44.29	1.36	2.91	1.84	9.02
Other reasons	63.29	1.92	5.36	3.15	12.93
Non-attached (do not want)	2481.46	79.17	54.59	39.20	2.92
(Long-term) future job starts	1.44	0.04	0.49	0.31	48.36
Other non-attached	2480.23	79.13	54.26	37.96	2.91

SOURCE: Author's calculations based on the LFS;
NOTES:

1. The observations from 2010 through 2011 are not considered in the sample to avoid biases resulting from the methodological break of the LFS;

2. The values are the quarterly averages from 1998:1 to 2018:1.

TABLE B3: Average quarterly transition rates at different time horizons, 1998-2018.

To ⎯⎯⎯ From	E	U	M	N
Two quarters apart				
U	.274	.536	.085	.104
	(.005)	(.008)	(.003)	(.004)
M	.195	.224	.307	.273
	(.006)	(.005)	(.004)	(.005)
N	.039	.018	.024	.919
	(.001)	(.001)	(.003)	(.004)
Three quarters apart				
U	.324	.471	.085	.119
	(.006)	(.009)	(.004)	(.005)
M	.239	.212	.270	.279
	(.007)	(.005)	(.005)	(.006)
N	.050	.021	.023	.906
	(.001)	(.001)	(.003)	(.004)
Four quarters apart				
U	.363	.419	.084	.134
	(.006)	(.009)	(.004)	(.005)
M	.268	.203	.240	.289
	(.007)	(.006)	(.007)	(.007)
N	.062	.023	.022	.893
	(.002)	(.001)	(.003)	(.004)

SOURCE: Author's calculations based on the LFS.
NOTES:

1. Standard errors in parentheses;

2. The observations from 2010 through 2011 are not considered in the sample to avoid biases resulting from the methodological break of the LFS;

3. Transition rates are calculated by matching individuals' responses two quarters, three quarters, and four quarters ahead, respectively.

Table B4: Average quarterly transition rates by detailed origin state, 1998-2018.

To ——— From	E	U	M	N
U subgroups				
U short-term	.249	.594	.077	.080
	(.006)	(.008)	(.003)	(.003)
U long-term	.135	.677	.096	.092
	(.004)	(.006)	(.004)	(.005)
M subgroups				
Inactive searcher	.163	.359	.294	.192
	(.010)	(.012)	(.010)	(.011)
Waiting	.288	.303	.272	.145
	(.015)	(.011)	(.011)	(.007)
Discouraged	.089	.206	.449	.256
	(.004)	(.005)	(.006)	(.007)
Personal reasons	.089	.184	.395	.332
	(.006)	(.007)	(.008)	(.009)
Other reasons	.132	.218	.330	.320
	(.006)	(.009)	(.010)	(.011)
N subgroups				
Future job starters	.385	.160	.112	.351
	(.033)	(.026)	(.022)	(.033)
Other non-attached	.026	.015	.024	.935
	(.002)	(.000)	(.003)	(.004)

Source: Author's calculations based on the LFS.

Notes:

1. Standard errors in parentheses;

2. The observations from 2010 through 2011 are not considered in the sample to avoid biases resulting from the methodological break of the LFS.

Table B5: Description of the explanatory variables used in the estimations.

Variable	Description
Age	Age of the individual in the $[15, 74]$ interval.
Age^2	Age of the individual squared.
Gender	Takes on the value 1 if male; 0 if female.
Marital status	Takes on the value 1 if married; 0 if single.
Education	Takes on the value 3 if higher education; 2 if secondary education; 1 if basic education; 0 if otherwise.
Region	Takes on the value 6 if resident at *Madeira*; 5 if resident at *Azores*; 4 if resident at *Alentejo*; 3 if resident at *Lisboa*; 2 if resident at *Centro*; 1 if resident at *Algarve*; 0 if resident at *North*.
Season	Takes on the value 3 if Autumn; 2 if Summer; 1 if Spring; 0 if Winter.

NOTE: For the categorical variables, the outcome corresponding to 0 is set to as the default category. Dummy variables for the origin state and the corresponding interactions are added in the unrestricted model.

Table B6: Likelihood-ratio test for the heterogeneity within subgroups of non-employment.

	Time period	
H_0	1998:1-2010:4	2011:1-2018:1
$U(ST) = U(LT)$	3415.48 (0.000)	2505.71 (0.000)
$M(W) = M(S) = M(P) = M(D) = M(O)$	1493.90 (0.000)	3069.78 (0.000)
$N(FJS) = N(O)$	271.14 (0.000)	110.26 (0.000)

SOURCE: Based on LFS data.
NOTE: $U(ST)$, $U(LT)$, $M(S)$, $M(W)$, $M(D)$, $M(P)$, $M(O)$, $N(FJS)$, $N(O)$ stand for short-term unemployed, long-term unemployed, marginally-attached searching, waiting, discouraged, personal reasons, other reasons, long-term future job starts, and other non-attached. The reported values are the observed likelihood-ratio test statistics for the respective H_0. The $p-$values are reported in parentheses.

TABLE B7: Likelihood-ratio test for the equivalence across sub-groups of non-employment.

	Time period	
H_0	1998:1-2010:4	2011:1-2018:1
$M(W) = U$	344.33 (0.000)	123.61 (0.000)
$M(S) = U$	137.56 (0.000)	378.45 (0.000)
$N(FJS) = U$	63.08 (0.002)	57.54 (0.004)

SOURCE: Based on LFS data.
NOTE: $M(W)$, $M(S)$, and $N(FJS)$ stand for marginally-attached searching, waiting, and long-term future job starts. The reported values are the observed likelihood-ratio test statistics for the respective H_0. The $p-$values are reported in parentheses.

TABLE B8: Multinomial logit likelihood ratio test for the equivalence between non-employment states, short-term non-employed (< 12 months).

	Time period	
H_0	1998:1-2010:4	2011:1-2018:1
$M = N$	4660.52 (0.000)	1648.64 (0.000)
$M = U$	2986.85 (0.000)	5181.99 (0.000)
$N = U$	62388.57 (0.000)	32115.77 (0.000)

SOURCE: Based on LFS data.
NOTE: The reported values are the observed likelihood-ratio test statistics for the respective H_0. The $p-$values are reported in parentheses.

C. Figures

Figure C.1: Classification diagram.
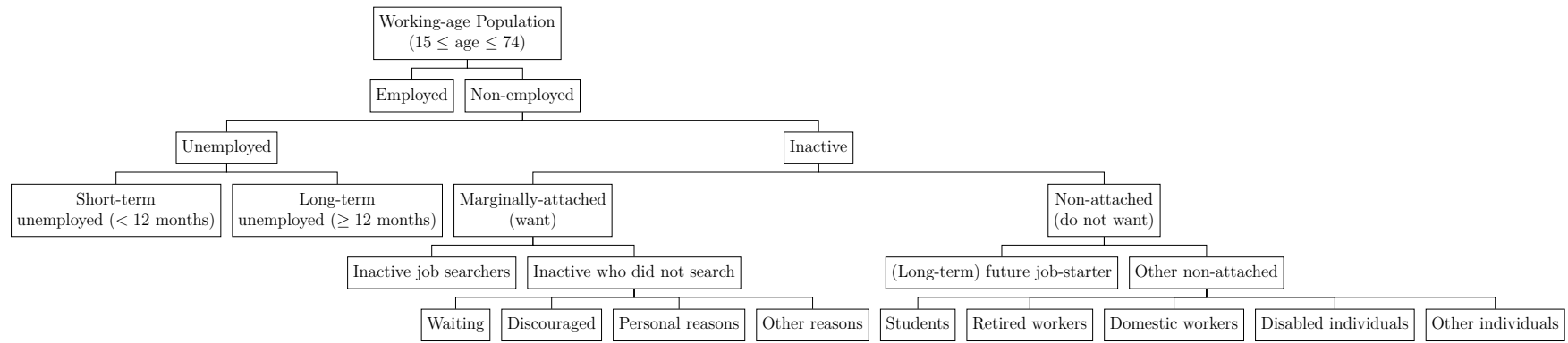
Note: The classification follows the algorithm in section 3.2.

Figure C.2: Transition rates by subgroups of inactivity, 1998-2018.

Source: Author's calculations based on the LFS.

Note: The series are a four-quarter moving-average to abstract from seasonality and high frequency movements. The shadings indicate recessions according to Rua (2017). The vertical line signals the survey redesign.

Figure C.3: Transition rates into employment by subgroups of the marginally-attached group, 1998-2018.
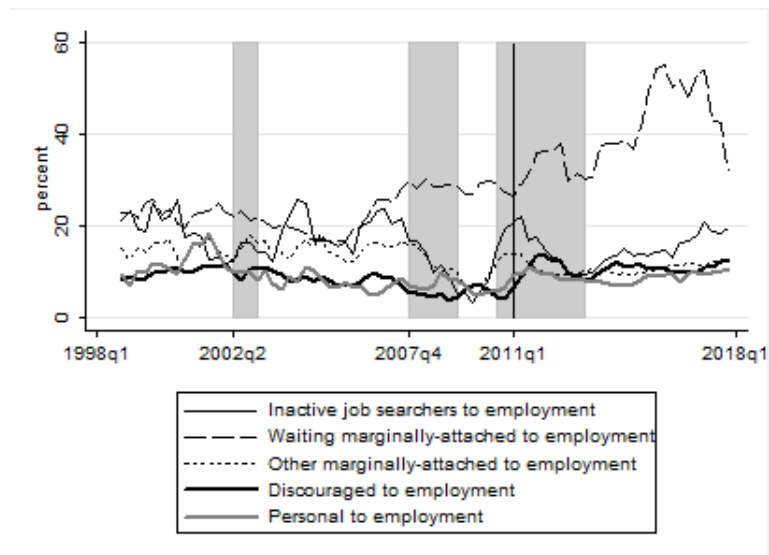
Source: Author's calculations based on the LFS.
Note: The series are a four-quarter moving-average to abstract from seasonality and high frequency movements. The shadings indicate recessions according to Rua (2017). The vertical line signals the survey redesign.

D. Estimation Results

TABLE D1: Multinomial logit estimation results, Marginally-attached and non-attached pool, 1998:1-2010:4.

Destination state	Unrestricted		Restricted	
	U	E	U	E
Demographics				
Age	1.331***	1.151***	1.336***	1.154***
	(.003)	(.002)	(.003)	(.002)
Age^2	.996***	.998***	.996***	.998***
	(.000)	(.000)	(.000)	(.000)
Male	1.299***	1.513***	1.310***	1.514***
	(.015)	(.015)	(.015)	(.015)
Married	.932***	1.147***	.949***	1.149***
	(.016)	(.017)	(.015)	(.017)
Education				
Basic	2.293***	1.148***	2.259***	1.149***
	(.057)	(.018)	(.052)	(.017)
Secondary	1.786***	.939***	1.762***	.937***
	(.049)	(.018)	(.045)	(.018)
Higher	5.126***	2.620***	4.802***	2.636***
	(.158)	(.061)	(.139)	(.060)
Origin state				
M	338.884***	30.497***	–	–
	(56.735)	(6.327)		
Interactions				
$M \times$ Age	.786***	.881***	–	–
	(.006)	(.009)		
$M \times$ Age^2	1.003***	1.001***	–	–
	(.000)	(.000)		
$M \times$ Male	1.0141	1.045	–	–
	(.038)	(.048)		

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Destination state	Unrestricted		Restricted	
	U	E	U	E
$M \times$ Married	.979	.862***	–	–
	(.043)	(.046)		
$M \times$ Basic	.536***	.780***	–	–
	(.039)	(.066)		
$M \times$ Secondary	.855*	1.050	–	–
	(.074)	(.107)		
$M \times$ Higher	.324***	.673***	–	–
	(.033)	(.078)		
Constant	.001***	.015***	.001***	.015***
	(.000)	(.001)	(.000)	(.001)
Observations	761546		761546	
Pseudo-R^2	0.1408		0.1286	

Source: Based on LFS data.

Notes:

1. Estimations on pooled data over 52 waves for individuals occupying the marginal-attachment and non-attachment (M and N) states in the origin state;

2. Dependent variable takes on values 1, 2, and 3, corresponding to three destination states: respectively, the pooled state comprising marginally-attached and non-attached (M and N), the employment state (E), and the unemployment state (U). Baseline category is remaining in the M and N pooled state;

3. The reported values are the relative-risk ratios. Robust standard errors in parentheses;

4. Seasonal and regional patterns are captured using 3 quarter and 6 region dummy variables, respectively.

5. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

Table D2: Multinomial logit estimation results, Marginally-attached and non-attached pool, 2011:1-2018:1.

Destination state	Unrestricted		Restricted	
	U	E	U	E
Demographics				
Age	1.423***	1.140***	1.409***	1.140***
	(.003)	(.002)	(.003)	(.002)
Age^2	.995***	.998***	.996***	.998***
	(.000)	(.000)	(.000)	(.000)
Male	1.420***	1.839***	1.395***	1.821***
	(.018)	(.017)	(.016)	(.016)
Married	.839***	1.378***	.842***	1.344***
	(.015)	(.018)	(.013)	(.016)
Education				
Basic	3.063***	1.127***	2.660***	1.132***
	(.109)	(.018)	(.079)	(.018)
Secondary	3.835***	1.213***	3.249***	1.198***
	(.141)	(.025)	(.101)	(.024)
Higher	4.389***	1.379***	3.526***	1.413***
	(.170)	(.031)	(.115)	(.030)
Origin state				
M	41.758***	.892	–	–
	(5.178)	(.131)		
Interactions				
$M\times$ Age	.859***	1.020***	–	–
	(.005)	(.007)		
$M\times$ Age^2	1.002***	.100***	–	–
	(.000)	(.000)		
$M\times$ Male	.901***	.887***	–	–
	(.024)	(.028)		

(Continued)

Destination state	Unrestricted		Restricted	
	U	E	U	E
$M \times$ Married	1.034	.781***	–	–
	(.036)	(.031)		
$M \times$ Basic	.437***	1.095	–	–
	(.030)	(.081)		
$M \times$ Secondary	.390***	.950	–	–
	(.028)	(.077)		
$M \times$ Higher	.346***	1.210**	–	–
	(.027)	(.105)		
Constant	.000***	.015***	.001***	.015***
	(.000)	(.001)	(.000)	(.001)
Observations	391042		391042	
Pseudo-R^2	0.129		0.120	

Source: Based on LFS data.

Notes:

1. Estimations on pooled data over 29 waves for individuals occupying the marginal-attachment and non-attachment (M and N) states in the origin state;

2. Dependent variable takes on values 1, 2, and 3, corresponding to three destination states: respectively, the pooled state comprising marginally-attached and non-attached (M and N), the employment state (E), and the unemployment state (U). Baseline category is remaining in the M and N pooled state;

3. The reported values are the relative-risk ratios. Robust standard errors in parentheses;

4. Seasonal and regional patterns are captured using 3 quarter and 6 region dummy variables, respectively.

5. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

Table D3: Multinomial logit estimation results, marginally-attached and unemployment pool, 1998:1-2010:4.

Destination state	Unrestricted		Restricted	
	E	N	E	N
Demographics				
Age	.985***	.888***	.986***	.895***
	(.004)	(.003)	(.003)	(.003)
Age^2	.100***	1.002***	.100***	1.002***
	(.000)	(.000)	(.000)	(.000)
Male	1.170***	.669***	1.235***	.697***
	(.016)	(.010)	(.016)	(.009)
Married	1.090***	1.075***	1.056***	1.052***
	(.018)	(.019)	(.016)	(.017)
Education				
Basic	.699***	.703***	.736***	.736***
	(.023)	(.022)	(.022)	(.021)
Secondary	.722***	.631***	.781***	.662***
	(.026)	(.024)	(.026)	(.022)
Higher	1.013	.412***	1.109***	.441***
	(.039)	(.018)	(.040)	(.018)
Origin state				
M	.537***	.306***	–	–
	(.114)	(.053)		
Interactions				
$M\times$ Age	.982*	1.058***	–	–
	(.010)	(.009)		
$M\times$ Age^2	1.000**	.999***	–	–
	(.000)	(.000)		
$M\times$ Male	1.160***	1.299***	–	–
	(.052)	(.049)		

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Destination state	Unrestricted			Restricted	
	E	N		E	N
$M \times$ Married	.895**	.906**		–	–
	(.046)	(.039)			
$M \times$ Basic	1.185*	1.277***		–	–
	(.106)	(.091)			
$M \times$ Secondary	1.287**	1.249**		–	–
	(.135)	(.111)			
$M \times$ Higher	1.345**	1.477***		–	–
	(.155)	(.160)			
Constant	2.681***	9.209***		2.299***	7.577***
	(.194)	(.685)		(.155)	(.507)
Observations	157732			157732	
Pseudo-R^2	0.049			0.041	

Source: Based on LFS data.

Notes:

1. Estimations on pooled data over 52 waves for individuals occupying the marginal-attachment and unemployment (M and U) states in the origin state;

2. Dependent variable takes on values 1, 2, and 3, corresponding to three destination states: respectively, the pooled state comprising marginally-attached and unemployment (M and U), the employment state (E), and the non-attachment (N). Baseline category is remaining in the M and U pooled state;

3. The reported values are the relative-risk ratios. Robust standard errors in parentheses;

4. Seasonal and regional patterns are captured using 3 quarter and 6 region dummy variables, respectively.

5. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

Table D4: Multinomial logit estimation results, marginally-attached and unemployment pool, 2011:1-2018:1.

Destination state	Unrestricted		Restricted	
	E	N	E	N
Demographics				
Age	1.019***	.659***	1.030***	.688***
	(.003)	(.002)	(.003)	(.002)
Age^2	1.000***	1.005***	1.000***	1.005***
	(.000)	(.000)	(.000)	(.000)
Male	1.147***	.614***	1.255***	.661***
	(.015)	(.009)	(.014)	(.008)
Married	1.107***	1.279***	1.110***	1.276***
	(.017)	(.025)	(.015)	(.021)
Education				
Basic	1.154***	.824***	1.231***	.915**
	(.043)	(.035)	(.040)	(.032)
Secondary	1.342***	.790***	1.443***	.906***
	(.052)	(.036)	(.049)	(.033)
Higher	1.590***	.715***	1.780***	.851***
	(.064)	(.035)	(.063)	(.033)
Origin state				
M	.488***	.067***	–	–
	(.079)	(.009)		
Interactions				
$M\times$ Age	.984**	1.160***	–	–
	(.007)	(.007)		
$M\times$ Age^2	1.000***	.998***	–	–
	(.000)	(.000)		
$M\times$ Male	1.270***	1.340***	–	–
	(.041)	(.037)		

(Continued)

Destination state	Unrestricted		Restricted	
	E	N	E	N
$M\times$ Married	1.007	.982	–	–
	(.039)	(.035)		
$M\times$ Basic	1.048	1.406***	–	–
	(.083)	(.100)		
$M\times$ Secondary	.872	1.581***	–	–
	(.074)	(.121)		
$M\times$ Higher	1.037	1.919***	–	–
	(.094)	(.160)		
Constant	.619***	1476.300***	.399***	666.689***
	(.044)	(112.598)	(.025)	(41.820)
Observations	188079		188079	
Pseudo-R^2	0.106		0.090	

Source: Based on LFS data.

Notes:

1. Estimations on pooled data over 29 waves for individuals occupying the marginal-attachment and unemployment (M and U) states in the origin state;

2. Dependent variable takes on values 1, 2, and 3, corresponding to three destination states: respectively, the pooled state comprising marginally-attached and unemployment (M and U), the employment state (E), and the non-attachment (N). Baseline category is remaining in the M and U pooled state;

3. The reported values are the relative-risk ratios. Robust standard errors in parentheses;

4. Seasonal and regional patterns are captured using 3 quarter and 6 region dummy variables, respectively.

5. * denotes significance at 10% level; ** denotes significance at 5% level; *** denotes significance at 1% level.

Table D5: Hausman-Mcfadden test for Independence of Irrelevant Alternatives (IIA) assumption, marginally-attached and non-attached pool.

		1998:1-2010:4		
Omitted outcome	χ^2	Degrees-freedom	$p-$value	Evidence
M and N pool	-1980.696	32	–	for H_0
E	470.671	32	0.000	against H_0
U	10.985	32	1.000	for H_0
Observations		761546		
		2011:1-2018:1		
Omitted outcome	χ^2	Degrees-freedom	$p-$value	Evidence
M and N pool	-5280.901	32	–	for H_0
E	145000	32	0.000	against H_0
U	-108.676	32	–	for H_0
Observations		391042		

Source: Based on LFS data.
Notes:

1. H_0: Odds(Outcome-i *versus* Outcome-j) are independent of other alternatives, $i, j = 1, 2, 3, i \neq j$;

2. A significant test is evidence against H_0;

3. If $\chi^2 < 0$, the estimated model does not meet asymptotic assumptions. A negative result is evidence that IIA is not violated.

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TABLE D6: Hausman-Mcfadden test for Independence of Irrelevant Alternatives (IIA) assumption, marginally-attached and unemployed pool.

		1998:1-2010:4		
Omitted outcome	χ^2	Degrees-freedom	$p-$value	Evidence
M and U pool	-104.884	32	–	for H_0
E	71.176	32	0.000	against H_0
N	102.616	32	0.000	against H_0
Observations		157732		
		2011:1-2018:1		
Omitted outcome	χ^2	Degrees-freedom	$p-$value	Evidence
M and U pool	-225.927	32	–	for H_0
E	1217.273	32	0.000	against H_0
N	-1439.511	32	–	for H_0
Observations		188079		

SOURCE: Based on LFS data.
NOTES:

1. H_0: Odds(Outcome-i *versus* Outcome-j) are independent of other alternatives, $i, j = 1, 2, 3, i \neq j$;

2. A significant test is evidence against H_0;

3. If $\chi^2 < 0$, the estimated model does not meet asymptotic assumptions. A negative result is evidence that IIA is not violated.

Table D7: Binary logit tests description.

Test mark	Description
★★	Transition rate statistically significantly greater relative to short-unemployed, *ceteris paribus* (at 95% confidence level).
★	Transition rate statistically significantly equal relative to short-unemployed, *ceteris paribus* (at 95% confidence level).
♣♣	Transition rate statistically significantly greater relative to unemployed, *ceteris paribus* (at 95% confidence level).
♣	Transition rate statistically significantly equal relative to unemployed, *ceteris paribus* (at 95% confidence level).
▲▲	Transition rate statistically significantly greater relative to long-unemployed, *ceteris paribus* (at 95% confidence level).
▲	Transition rate statistically significantly equal relative to long-unemployed, *ceteris paribus* (at 95% confidence level).

NOTE: Only the test concerning the highest transition rate is displayed.

TABLE D8: Binary logit estimation results and equivalence testing across non-employment subgroups.

	Model with seasonal and regional controls	Model with individual controls
Status		
U, short-term	6.372***	4.729***
	(.102)	(.104)
U, long-term	3.671***	2.674***
	(.053)	(.053)
M, searched	3.522***▲▲	2.765***▲▲
	(.158)	(.130)
M, waiting	9.542***★★	7.066***★★
	(.581)	(.444)
M, discouraged	2.499***	2.036***
	(.060)	(.053)
M, personal reasons	2.211***	1.832***
	(.061)	(.056)
M, other reasons	2.313***	1.867***
	(.050)	(.051)
N, future job starter	9.888***★★	7.203***★★
	(1.867)	(1.375)
N, student	.757***	.664***
	(.013)	(.018)
N, retired	*Excluded*	*Excluded*
N, domestic	1.345***	1.417***
	(.024)	(.028)
N, disabled	.536***	.459***
	(.018)	(.016)
N, other	2.207***	1.759***
	(.055)	(.048)
Demographics		
Age	–	1.038***
		(.002)
Age^2	–	1.000***
		(.000)
Male	–	1.600***
		(.016)
Married	–	1.225***
		(.015)
Education		
Basic	–	1.027*
		(.019)
Secondary	–	1.128***
		(.025)
Higher	–	1.259***
		(.030)
Constant	.110***	.054***
	(.002)	(.003)
Observations	388548	388548
Pseudo-R^2	0.081	0.091

SOURCE: Based on LFS data.
NOTES:

1. Estimations on pooled data over 29 waves for individuals occupying the non-employment group in the origin state.

2. Dependent variable takes on values 0 and 1, corresponding to two destination states: respectively, the pooled non-employment state ($\bar{E}$), and the employment state (E). Baseline category is remaining in the pooled non-employment state.

3. The reported values are the odd-ratios. Robust standard errors in parentheses;

4. Seasonal and regional patterns are captured by 3 quarter and 6 regional dummy variables;

5. Significance levels: 10% level *; 5% level **; 1% level ***;

6. Equivalence tests: ★★ denotes coefficient statistically significantly greater relative to short-unemployed; ★ coefficient statistically significantly equal relative to short-unemployed; ♣♣ coefficient statistically significantly greater relative to unemployed; ♣ coefficient statistically significantly equal relative to unemployed; ▲▲ coefficient statistically significantly greater relative to long-unemployed; ▲ coefficient statistically significantly equal relative to long-unemployed.