The measurement of labour market slack: An empirical analysis for Portugal

Fernando Martins
Banco de Portugal
Universidade Lusíada de Lisboa
REM - Research in Economics and Mathematics, UECE

Domingos Seward
Banco de Portugal

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Abstract
This paper presents a perspective on the measurement of labour market slack in Portugal based on the degree of attachment of several groups of non-employed individuals. We discuss the adequacy of the conventional criteria used for the measurement of unemployment. Following the relevant strand of literature on this topic, we apply a classification of labour market status based on the transition behaviour of non-employed individuals. We conclude that some subgroups in inactivity display a transition behaviour into employment which is closer to the unemployed. This suggests that the classification of some individuals as inactive might not be adequate, since they show considerable attachment to the labour market and we reject the equivalence relative to their inactive counterparts. (JEL: C81, E24, J20)

1. Introduction

The recovery experienced by the Portuguese economy since 2013 has occurred in parallel with a substantial improvement in labour market conditions. The unemployment rate has decreased significantly, reaching the levels observed in 2003, while employment has increased back to pre-crisis levels. In spite of the improving labour market conditions, wage growth remains below the levels one would expect considering the cyclical position of the economy and the decrease in labour market slack. Indeed, whereas the unemployment rate has followed a decreasing

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E-mail: fmartins@bportugal.pt; dseward@bportugal.pt

path for several years, wage growth remains lower than it was before the global financial crisis for equivalent levels of unemployment (OECD, 2018). This background of low unemployment and modest wage inflation has been referred to as an economic “puzzle". One the explanations pointed out is related with the inability of the headline unemployment rate to capture the true extent of labour market slack (see, *e.g.* Yellen, 2014).

The evidence shows that the non-employed population appears to be heterogeneous. While the distinction between the employed and the non-employed is straightforward, the boundary between the unemployed and the inactive is difficult to trace. For example, 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. On the other hand, other inactive persons show little or no attachment to the labour force, namely by expressing no desire to work. Most of these individuals are less likely to find a job compared to those who have recently become unemployed, but the examination of longitudinal data on worker flows suggests that some subgroups within inactivity are at least as likely to find a job 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 periods of economic expansion. As discussed by Jones and Riddell (1999, 2006), one important implication for economic policy is that any effort towards measuring the degree of slack in the labour market by dichotomising the non-employed population into "unemployment" and "inactivity" is unable to comprehensively capture the complexity of labour market dynamics.

This paper presents a perspective on the measurement of labour market slack in Portugal based on the degree of attachment of several groups of individuals in the labour market. In this context, we propose an allocation of individuals across the three conventional states (employment, unemployment, and inactivity). We also discuss the adequacy of the conventional criteria used for the measurement of unemployment. Following the relevant strand of literature on this topic, we apply a classification of labour market status based upon the information on the transition behaviour of non-employed individuals.

2. The dataset

The results presented are based upon the Portuguese Labour Force Survey[1] (LFS), a household survey conducted quarterly by Statistics Portugal (*Instituto Nacional de Estatística*), with the goal of characterising the Portuguese labour market.

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, Statistics Portugal provides quarterly estimates for the stocks of employment, unemployment, and inactivity, which in turn are used for computing several indicators, such as the unemployment rate.

Each quarter, Statistics Portugal surveys approximately 22,000 households. The total sample is composed of six sub-samples which follow a rotation scheme, whereby each quarter 1/6 of the sample is rotated out and the remaining 5/6 are kept on the sample. Thus, once selected into the LFS sample, households should be interviewed for six consecutive quarters. Considering this feature of the sample, one can observe the labour force status for 5/6 of the respondents included in the sample in adjacent quarters, which enables the computation of worker flows and transition rates across states.[2]

In this article, we have used the LFS microdata for the period ranging from 1998:1 to 2019:3.

3. The measurement of the degree of labour market slack

The unemployment rate is the most commonly used measure of labour market slack. It is defined as the ratio between the number of unemployed individuals over the labour force. Labour Force Surveys (LFS) constitute the main source of data for the estimation of the number of unemployed individuals and their characterisation. Labour market 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 straightforward, the boundary between the unemployed and the inactive is less clearcut.

According to the Portuguese LFS, which follows the general guidelines set by the International Labour Organization (ILO), an unemployed person must fulfil three criteria: (*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.[3] The classification relies on the degree of attachment to the labour market, which is based crucially on the

1. In Portuguese, *Inquérito ao Emprego*.

2. See INE (2015) for additional information regarding the methodology of the LFS and the statistical inference procedure used for the construction of the sample. For a detailed description of the method used for calculating the gross worker flows and the transition rates, see Martins and Seward (2019, p. 34–35).

3. Those individuals which have not searched but are due to start work in the next three months are also included.

job search criterion. However, such a requirement may not be sufficient to completely capture the degree of slack contained in the labour market. The job 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 (Jones and Riddell, 1999, 2006).

In addition, the non-employed population seems to be a particularly heterogeneous group. By adopting a classification of labour market status using the information obtained from the LFS (Table 1), we conclude that some persons classified as inactive can be considered close to unemployment if, for example, 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. On the other hand, other inactive individuals show little or no attachment to the labour market, either because they display little marketable skills or because they do not desire to work. A group classified as inactive which has been the subject of increasing policy analysis is the so-called marginally-attached individuals, which are those individuals that want to work, but who are not actively searching for a job. Within the group of marginally-attached individuals, one can single out the group of discouraged workers, which comprises those individuals which want to work, but do not report actively searching for a job due to economic reasons (Table 1).[4]

In this context, unemployment may not be a sufficient metric to assess the degree of labour market slack if the requirements do not sort individuals appropriately relative to their willingness to work and/or their chance of finding a job, *i.e.* if considerable fractions of the non-employed population which do not satisfy the requirements to be classified as unemployed, would answer in a similar way when finding a given job vacancy.[5]

In practice, many non-employed persons become employed without being recorded in unemployment. Table 2 summarises the average quarterly employment inflows disaggregated by several subgroups of origin, over the period from 1998:1 to 2019:3.[6] We observe that indeed employment inflows originating from inactivity are substantial, and represent on average 76 thousand individuals each quarter. This figure compares with an average of 65 thousand individuals originating from unemployment. In particular, we observe that the transition pattern differs considerably between the inactivity subgroups. For example, 13.4% of the marginally-attached (those that express the desire to work) move into employment each quarter on average. On the other hand, the non-attached workers (those that do not desire to work) are much less likely to move into employment (3.0%). 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 (55.9 thousand each quarter on average). In addition, differences among the

4. Among the reasons for not actively searching for work is the belief that no work is available.

5. See, *e.g.* Jones and Riddell (1999, 2006) and Schweitzer (2003) for interesting discussions on this issue.

6. The LFS is based upon a probabilistic sample. Therefore, small aggregates tend to be estimated with lower precision. In this context, the values presented in Table 2 should be interpreted with some caution.

unemployed are noteworthy. As expected, the short-term unemployed are much more likely to move into employment than the long-term unemployed (25.7% *versus* 14.3%).

Such apparent differences in the employability of the above-mentioned labour market groups are also associated to differences in some socio-demographic characteristics (Table 3). In this context, we observe that the marginally-attached exhibit levels of education considerably higher than the non-attached and much closer to the unemployed (only 4.8% of the marginally-attached have no education, which compares with a value of 16.7% for the non-attached, and of 3.3% for the unemployed). Likewise, 23.0% of the marginally-attached are included in the 25 to 34 years-old cohort *vis-à-vis* 4.7% of the non-attached. We also observe that the marginally-attached tend to be on average less time out of employment in comparison with the non-attached (on average 15.4% of the marginally-attached are out of employment for less than a year, whereas only 2.3% of the non-attached display periods out of employment of less than a year).

Regarding the wages earned once these individuals become employed, the marginally-attached report a median net wage comparable to that of the unemployed and very close to the one reported by the long-term unemployed.[7] On the other hand, the reported median net wage by those inactive individuals that do not express desire to work is considerably lower, which is a further indication of heterogeneity among the inactive population.

We also notice that three inactive subgroups are particularly relevant in terms of their estimated transition rates into employment: the inactives who search for work, the inactives who report “waiting" as a reason for not having searched, and the inactives who are due to start a job in more than three months. These subgroups also display sociodemographic characteristics which are closer to the unemployed, distinguishing them from the remaining inactives. In particular, these subgroups exhibit higher levels of education in comparison to the remaining inactives, they are younger (with particular relevance of the 25 to 34 years-old cohort), they remain out of employment for less time, and they find on average a higher proportion of open-ended contracts, as well as higher entry net wages.

The aforementioned groups of inactivity are quantitatively relevant and could thus affect the perspective on the amount of underutilised labour supply in the market. In the data, the marginally-attached represent, on average, 6.5% of the non-employed population, whereas the discouraged workers account for 1.7% (Table 2). 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 may serve to enlarge the pool of unemployed as an important potential source of labour supply.

7. See Martins and Seward (2019, p. 37) for a detailed analysis of the reported median net wages once the non-employment individuals find a job.

Status	Abbreviation	Adopted definition
1. Unemployment	U	Non-employed individuals who did not work during the reference week, are available to work during the reference week or within the next two weeks, and have actively searched for work during the reference week or within the previous three weeks (the individuals which have not searched but are due to start work in the next three months are also included).
Short-term unemployment	$U(ST)$	Unemployed for less than 12 months.
Long-term unemployment	$U(LT)$	Unemployed for more than 12 months.
2. Marginally-attached	M	Inactive individuals who to want work.
Inactives who search	$M(S)$	Inactive individuals who search for work (includes individuals which search passively).
Inactives who wait	$M(W)$	Inactive individuals who report “waiting" as a reason for not searching for work (includes workers in temporary layoff).
Discouraged	$M(D)$	Inactives who report economic reasons not searching for work (believe there are no jobs available, are too young/old, do not have enough education, do not know how to find a job or consider that it is not worth searching).
Personal reasons	$M(P)$	Inactives who report personal reasons for not searching for work (ilness or inability, need to take care after children/disabled/elderly or other personal reasons).
Other marginally-attached	$M(O)$	Inactives who report studying or training, retirement, and other reasons for not searching for work.
3. Non-attached	N	Inactives who do not want (nor search for) work.
Long-term future job starters	$N(FJS)$	Inactives who will start a job in more than three months (or within three months but not available to start work during the reference week or the following two weeks).
Other non-attached	$N(O)$	Other non-attached individuals (includes students, retired workers, domestic workers, disabled individuals and others).

TABLE 1. Definitions of the selected non-employed subgroups

Status	Stocks (thousands)	Fraction of non-employment (%)	Flows into employment (thousands)	Fraction of new employment created (%)	Transition rates into employment (%)
1. Unemployment	445.3	14.0	65.0	46.7	19.8
Short-term unemployed	203.0	6.4	38.1	28.8	25.7
Long-term unemployed	242.1	7.5	26.8	17.9	14.3
2. Marginally-attached (want)	208.4	6.5	20.0	13.4	13.4
Inactive searcher	14.0	0.4	1.7	1.1	16.4
Waiting	23.1	0.8	4.5	4.0	31.0
Discouraged	55.8	1.7	4.4	2.8	9.7
Personal reasons	47.1	1.5	3.3	2.1	9.3
Other reasons	68.3	2.1	6.1	3.6	13.2
3. Non-attached (do not want)	2,468.4	79.5	55.9	39.9	3.0
(Long-term) future job starters	1.4	0.1	0.5	0.4	36.4
Other non-attached	2,467.2	79.5	55.6	39.6	3.0

TABLE 2. Summary statistics for selected non-employed subgroups, 1998:1-2019:3

Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The values are the quarterly averages from 1998:1 to 2019:3. The observations from 2010 to 2011 are not considered in the calculations to avoid possible effects resulting from the methodological change of the LFS in 2011:1.

	Unemployed			Marginally-attached			Non-attached	
	Total	Short-term Unemployed	Long-term Unemployed	Total	*of which:* Search for work	Waiting	Total	*of which:* Future job starters[1]
by Education								
No education	3.3	2.8	3.7	4.8	4.2	3.3	16.7	6.1
Basic education	63.4	59.1	67.1	68.1	61.9	64.2	64.8	55.8
Secondary education	20.2	22.3	18.5	18.0	22.0	18.2	13.6	23.5
Higher education	13.1	15.7	10.7	9.0	11.9	14.3	4.9	14.6
by Age Cohort								
15-24	22.3	30.8	14.1	25.7	23.8	21.7	27.7	30.2
25-34	26.9	30.0	24.1	23.0	28.3	27.9	4.7	26.9
35-44	21.4	19.5	23.4	18.6	20.3	22.4	5.0	16.7
$\geq$45	29.4	19.7	38.4	32.8	27.6	28.0	62.7	26.2
by Gender								
Female	52.9	53.0	53.2	62.4	61.5	56.9	60.2	48.3
Male	47.1	47.0	46.8	37.6	38.5	43.1	39.8	51.7
by Time Out of Employment								
$<$1 year	22.3	–	–	15.4	20.0	30.7	2.3	24.7
1-2 years	27.3	–	–	19.9	25.7	27.0	4.7	25.7
$\geq$2 years	50.4	–	–	64.7	54.4	42.3	93.0	49.6
by Type of Contract[2]								
Open-ended contract	13.6	12.7	15.3	16.2	17.9	17.7	15.9	26.3
Other types of contracts	86.4	87.3	84.7	83.8	82.1	82.3	84.1	73.7
Net wages once employed[3]	520.0	550.0	500.0	500.0	505.0	525.0	485.0	600.0

TABLE 3. Sociodemographic characterisation and reported median net wages by labour market groups, 1998:1-2019:3

Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The values are the quarterly averages of the proportions (%) in each labour market group by sociodemographic characteristics in the period from 1998:1 to 2019:3. The observations from 2010 to 2011 are not considered in the calculations to avoid possible effects resulting from the methodological change of the LFS in 2011:1.

(1) Subgroup comprised by the inactive individuals which are due to start a job in more than three months.

(2) The values are the quarterly averages of the proportions (%) in each labour market group which either obtain work with an open-ended contract or with another type of contract (*e.g.* fixed-term contract), in the period from 1998:1 to 2019:3.

(3) The values are the reported median net wages in euros by each labour market group once the individuals transition into employment, in the period from 2012:1 to 2019:3.

4. Literature review

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

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

The findings obtained by these authors inspired several statistical analyses of the equivalence of the unemployment and inactivity categories. In their seminal article, Flinn and Heckman (1983) 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.[8] The authors proposed a statistical framework for testing the equivalence of labour market states in longitudinal data, based on a duration of status econometric approach. The authors test for the equivalence between the unemployment and inactive states for young white American males and find evidence that rejects this hypothesis.

Tano (1991) tests the hypothesis that unemployment and inactivity 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 and female highschool graduates, by employing a duration econometric model, with mixed results by gender.

Jones and Riddell (1999, 2006) extended the former literature by examining the transition behaviour within the unemployed and the inactive groups for the USA and Canada. The authors examine the equivalence between groups by applying multinomial

8. 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.

and binary logit models for the transition behaviour of individuals. The authors find that the group of marginally-attached workers (comprising those inactives who do not search, but want work) constitutes a distinct state in the labour market. The authors discuss the adequacy of the unemployment measurement criteria, since they find that some subgroups in inactivity display a transition behaviour closer to unemployment.[9] Schweitzer (2003) obtains similar results for the United Kingdom.

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. 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 equivalent to the unemployed when their last search effort was done not long before the four-week requirement, which highlights the arbitrariness of the criterion.

Centeno and Fernandes (2004) study the heterogeneity in the Portuguese labour market. The data used in their work is drawn from the Portuguese LFS for the period ranging from 1992:1 to 2003:4. The authors adopt a duration econometric framework to model transition probabilities. The results suggest that the marginally-attached group is a distinct labour market state in Portugal. These findings have been confirmed by Centeno *et al.* (2010), with implications for the Non-Accelerating Inflation Rate of Unemployment (NAIRU).

Regarding the 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. Likewise, other investigations conclude that the short-term and the long-term unemployed exhibit substantial differences in their transition behaviour to employment (see Kroft *et al.*, 2012 and Eriksson and Rooth, 2014).

5. Heterogeneity in the Portuguese labour market

5.1. *Statistical framework*

The adopted statistical framework folows the seminal contribution by Flinn and Heckman (1983), subsequently extended by Jones and Riddell (1999, 2006), by 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.[10] We assume that the transition of workers across labour market states

9. For instance, the subgroup comprising those individuals which report “waiting" as a reason for not having searched for a job.

10. For the purpose of this work, Y_t is assumed discrete and takes on values corresponding to k mutually-exclusive and exhaustive states.

is represented by a discrete Markov chain of order 1. Therefore, the data generating process, $\{Y_t\}_{t=1}^{T}$, follows:

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

wherein $i = 1, 2, \dots, k$ indexes the observed status in the Y_t domain. The process represented by equation (1) respects the Markov property.[11]

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

$$p_{ij,t} = \Pr(Y_t = j|Y_{t-1} = i), \; i, j = 1, 2, \dots, k\,. \tag{2}$$

We start by considering four labour market states ($k = 4$). The transitions across employment (E), unemployment (U), the group of the marginally-attached (M), and the group of the non-attached (N) is summarised by the four-by-four transition matrix P, where the ij^{th} element, p_{ij}, represents the probability of a person moving from state $i \in \{E, U, M, N\}$ in the current quarter to state $j \in \{E, U, M, N\}$ in the following quarter:

$$P_t = \begin{pmatrix} p_{EE} & p_{EU} & p_{EM} & p_{EN} \\ p_{UE} & p_{UU} & p_{UM} & p_{UN} \\ p_{ME} & p_{MU} & p_{MM} & p_{MN} \\ p_{NE} & p_{NU} & p_{NM} & p_{NN} \end{pmatrix}_t . \tag{3}$$

In this paper, we apply an evidence-based categorisation of labour market status by exploiting the information on the results of the transition behaviour of non-employed individuals.[12] Therefore, we classify individuals into the same state if they exhibit equivalent behaviour regarding subsequent state.[13]

5.2. Descriptive analysis

Table 4 shows the estimated quarterly 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 19.8%, almost 6 percentage points above that of M (13.4%). Moreover, there is a striking difference between the M and N as origin groups, with the transition rate from N to E averaging only 3.0%. In addition, for each non-employment destination state, the transition rates between origin groups U and M and between M and N differ considerably: $\hat{p}_{MN} = 27.4\% > \hat{p}_{UN} = 8.3\%$ and $\hat{p}_{MU} = 22.8\% > \hat{p}_{NU} = 1.5\%$.

11. Thus, the observed values for Y_t depend only on the current status. Such assumption is rather strict and whenever possible should be tested. We have conducted a robustness analysis to this assumption by restricting the sample to those individuals in non-employment for less than twelve months and conclude that the findings hold.

12. The pioneering authors of this approach include Flinn and Heckman (1983) and Jones and Riddell (1999, 2006). See Centeno and Fernandes (2004) and Centeno *et al.* (2010) for applications to Portugal.

13. For instance, one may consider two groups to be equally attached to the labour 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.

From the examination of the transition rates over the sample period (Figure 1), we conclude that (i) these exhibit, in general, considerable stability over time, with the exception of those into employment for which the cyclical pattern is very marked, (ii) the ordering of the transition rates is the same in every 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 $\hat{p}_{NN} > \hat{p}_{MN} > \hat{p}_{UN}$, and ($iii$) 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-employed individuals conveys substantial information about their attachment to the labour market.

In order to examine the extent of heterogeneity within the labour market states considered, we compute the average transition rates by detailed origin state (Table 4). We perform the conventional split of U by duration. The short-term unemployed are almost twice as likely to move into E (25.7%) relative to the long-term unemployed (14.3%). Conversely, the long-term unemployed have a higher chance to remain unemployed or to move into inactivity in the following quarter.

Furthermore, we find important heterogeneity within the M group. The striking result is that the "waiting" subgroup shows a transition rate into E (31.0%) considerably higher than the other subgroups, as well as a lower transition rate into N (13.9%). Moreover, the subgroup comprising those M individuals which report having searched for a job also displays significant attachment to the labour market, since 16.4% of these individuals move to employment each quarter on average, which is above the transition rate estimated for the long-term unemployed (14.3%).[14]

A measurement issue relates to those individuals who are not searching for work but who have found a job due to start more than three months after the survey interview[15]. We refer to these “officially" inactive but highly attached non-employed as long-term future job starters. In Portugal, as in many other countries, these non-employed are classified as inactive even though they display the largest estimated transition rate into E of all the subgroups considered in this study (36.4%).[16] In Portugal, this subgroup of N amounts to 1.4 thousand individuals each quarter on average (Table 2).

14. On the other hand, these non-employed also move to non-attachment quite often (20.0%); still, this figure is considerably below the corresponding transition rate displayed by most of their marginally-attached counterparts.

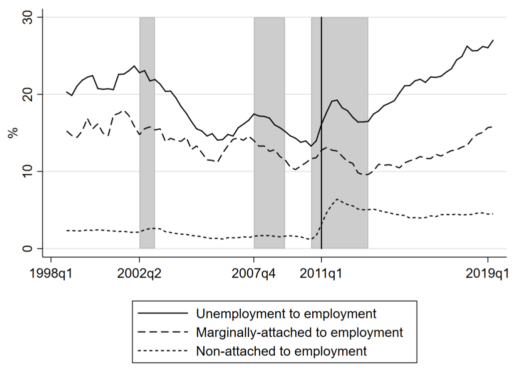
15. Those that are due to start a job within three months but who do not meet the availability criterion are also included.

16. However, they also exhibit a high transition rate into inactivity (33.3%), which makes it hard to evaluate this classification practice based on these data.

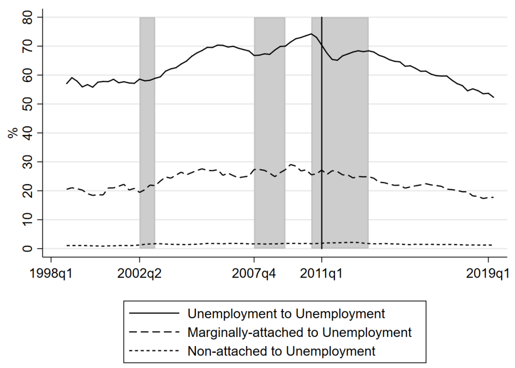
To / From	E	U	M	N
E	0.963	0.015	0.005	0.016
	(0.002)	(0.001)	(0.000)	(0.001)
U	0.198	0.625	0.094	0.083
	(0.005)	(0.007)	(0.003)	(0.004)
subgroups of U				
$U(ST)$	0.257	0.583	0.082	0.078
	(0.006)	(0.008)	(0.002)	(0.003)
$U(LT)$	0.143	0.665	0.103	0.089
	(0.004)	(0.006)	(0.004)	(0.004)
M	0.134	0.228	0.364	0.274
	(0.003)	(0.005)	(0.004)	(0.005)
subgroups of M				
$M(S)$	0.164	0.348	0.295	0.200
	(0.009)	(0.011)	(0.010)	(0.010)
$M(W)$	0.310	0.295	0.263	0.139
	(0.016)	(0.012)	(0.011)	(0.007)
$M(D)$	0.097	0.208	0.436	0.259
	(0.004)	(0.005)	(0.006)	(0.006)
$M(P)$	0.093	0.182	0.393	0.331
	(0.005)	(0.007)	(0.007)	(0.008)
$M(O)$	0.132	0.213	0.325	0.330
	(0.006)	(0.008)	(0.009)	(0.010)
N	0.030	0.015	0.029	0.926
	(0.002)	(0.000)	(0.003)	(0.004)
subgroups of N				
$N(FJS)$	0.364	0.179	0.127	0.333
	(0.034)	(0.025)	(0.024)	(0.033)
$N(O)$	0.030	0.015	0.029	0.926
	(0.002)	(0.000)	(0.003)	(0.004)

TABLE 4. Average quarterly transition rates by labour market groups, 1998:1-2019:3

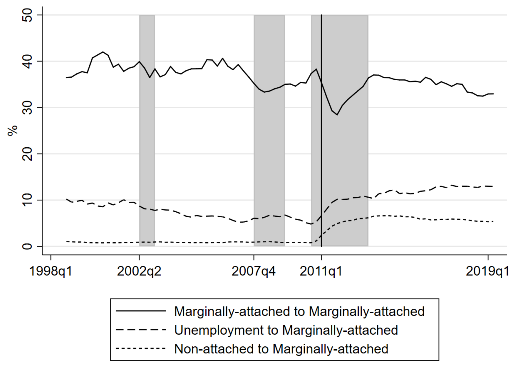
Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The values are the quarterly averages from 1998:1 to 2019:3. The standard errors are in parentheses. The observations from 2010 to 2011 are not considered in the calculations to avoid possible effects resulting from the methodological change of the LFS in 2011:1.



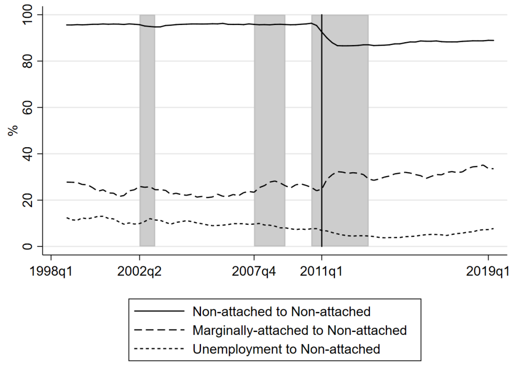
(A) Transition rates into employment



(B) Transition rates into unemployment



(C) Transition rates into marginal-attachment



(D) Transition rates into non-attachment

FIGURE 1: Average quarterly transition rates by groups of inactivity, 1998:1-2019:3

Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The series are a four-quarter moving-average to abstract from the marked seasonal pattern. The shadings indicate recessions according to Rua (2017). The vertical line signals the methodological change of the LFS in 2011:1.

5.3. *Conditional assessment*

5.3.1. *Econometric model*

The average transition rates analysed so far consider individuals which differ on various characteristics. Therefore, it is crucial to assess whether the findings are essentially driven by compositional effects.[17] For this purpose, we estimate multinomial logit models (MLM) on the determinants of transitions across several labour market states.[18][19]

In logistic models, the probability of moving into a category is compared to the probability of being 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:[20]

$$f_j(\boldsymbol{x}_{h,t}) = \ln \frac{\Pr(Y_{h,t} = j | Y_{h,t-1} = i, \boldsymbol{x}_{h,t})}{\Pr(Y_{h,t} = j^* | Y_{h,t-1} = i, \boldsymbol{x}_{h,t})} = \alpha_j + \boldsymbol{x}'_h \boldsymbol{\beta}_j, \; j \neq j^* , \tag{4}$$

where h indexes the person, $Y_{h,t}$ denotes the first-order Markov chain for person h in period t, $\boldsymbol{x}_{h,t}$ refers to the vector of conditioning individual characteristics, α_j denotes a constant, and $\boldsymbol{\beta}_j$ denotes the vector of regression 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 the sample who belong to states M or N state in the first period, such that their three possible destinations are E, U or to remain in inactivity ($M+N$), and we estimate a multinomial logit regression (equation (4)).[21] The covariates refer to the personal and socio-economic characteristics of the respondent, as well as to a set of seasonal and regional dummy variables.[22] Afterwards, an unrestricted model is estimated by adding a dummy variable identifying the individuals who were originally in state M. The origin state dummy is interacted with each explanatory variable. In order to test for the equivalence between M and N, we employ a likelihood-ratio test, under

17. Such that different types of persons are more or less likely to belong to different groups than others (with an impact on the respective transition rates) or whether the findings still hold after controlling for such differences.

18. As opposed to Jones and Riddell (1999, 2006), we report the results from pooled multinomial logit regressions, since it has the advantage of increasing the sample size.

19. Such models will enable us to test whether two origin states are equivalent after controlling for the observable characteristics of the individuals.

20. In our model, we set $j^* = i$, *i.e.* we define the baseline outcome as the individual remaining in the previous state.

21. The models are estimated via the maximum likelihood procedure.

22. See Martins and Seward (2019, p. 41) for a detailed description of the covariates used in the regressions.

the null hypothesis that the groups are equivalent. The same reasoning is applied to test for the equivalence between other non-employed groups.[23]

5.3.2. *Discussion of results*

The results of the likelihood-ratio tests are reported in Table 5.[24]

	Time period	
H_0	1998:1-2010:4	2011:1-2019:3
$M = N$	9,021.85 (0.000)	5,720.34 (0.000)
$M = U$	2,816.79 (0.000)	6,759.55 (0.000)
$U = N$	121,896.63 (0.000)	84,699.43 (0.000)

TABLE 5. Likelihood-ratio tests in multinomial logit models for the equivalence between non-employment states

Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The reported values are the observed likelihood-ratio test statistics for the respective H_0. The p-values are reported in parentheses.

We reject the statistical equivalence between M and N, M and U, and N and U, in all the periods.[25] Such results provide evidence supporting the hypothesis that the group comprising the marginally-attached individuals is distinct from the non-attached, as well as rejecting the equivalence between the marginally-attached and the unemployed. Furthermore, we reject the pooling of the unemployed and the non-attached groups. Hence, these formal statistical tests generally corroborate the evidence found for the empirical transition rates.

We also test the heterogeneity within each of the analysed groups (Table 6) and conclude that: (i) within the unemployed, our results point towards a rejection of the equivalence between the short-term and the long-term unemployed, (ii) within the marginally-attached, the statistical evidence leads to the rejection of the equivalence between its subgroups, and (iii) within the non-attached group, we test and reject the null of equivalence between the future job starters and the other non-attached.

Lastly, we conduct statistical tests for the equivalence between subgroups across the conventional classification criteria (Table 7). The tests again lead us to reject the equivalence between all the states considered. However, one can argue that, to the extent that the tests reject pooling the states, this is mainly due to the fact that, for example, the probability of the subgroup of inactive individuals which report "waiting" ($M(W)$)

23. Since the LFS was subject to a survey redesign in 2011:1 (INE, 2015; Neves, 2014), we conduct the tests separately for each survey.

24. Considering the interest in the equivalence tests rather than on the interpretation of the estimated regressions, for the sake of space we do not report the estimated regressions in this paper. See Martins and Seward (2019, p. 46–49) for the detailed results of the regressions.

25. This finding can be inferred from the large values for the observed likelihood-ratio test statistic and respective p-values which are equal to 0.000 for all the conducted tests.

H_0	Time period 1998:1-2010:4	2011:1-2019:3
$U(ST) = U(LT)$	3,415.48 (0.000)	2,508.15 (0.000)
$M(W) = M(S) = M(P) = M(D) = M(O)$	1,493.90 (0.000)	3,116.98 (0.000)
$N(FJS) = N(O)$	257.63 (0.000)	111.20 (0.000)

TABLE 6. Likelihood-ratio tests in multinomial logit models for the equivalence between subgroups of the same non-employment status

Source: Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The reported values are the observed likelihood-ratio test statistics for the respective H_0. The p-values are reported in parentheses. $U(ST)$, $U(LT)$, $M(S)$, $M(W)$, $M(D)$, $M(P)$, $M(O)$, $N(FJS)$, and $N(O)$ stand for short-term unemployed, long-term unemployed, marginally-attached searching, waiting, discouraged, personal reasons, other reasons, long-term future job starters, and other non-attached, respectively.

moving into employment is higher than that of the unemployed. The same conclusion can be inferred for those future job starters classified as inactive ($N(FJS)$).

H_0	Time period 1998:1-2010:4	2011:1-2019:3
$M(W) = U$	344.33 (0.000)	124.04 (0.000)
$M(S) = U$	137.56 (0.000)	389.24 (0.000)
$N(FJS) = U$	63.08 (0.002)	56.99 (0.004)

TABLE 7. Likelihood-ratio tests in multinomial logit models for the equivalence between subgroups of different non-employment statuses

Source: Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes: The reported values are the observed likelihood-ratio test statistics for the respective H_0. The p-values are reported in parentheses. U, $M(W)$, $M(S)$, and $N(FJS)$ stand for the unemployed, the marginally-attached searching, the marginally-attached waiting, and the long-term future job starters.

5.3.3. *Limitations and robustness check*

The MLM specification imposes the independence of irrelevant alternatives assumption (IIA) (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 several aspects closer to inactivity than to E.[26]

Hausman and McFadden (1984) developed a test of the IIA. We conduct this test for the multinomial logit models applied to test for the equivalence between M and N, M and U, and N and U. We obtain mixed results for each outcome depending on the category omitted from the full model.[27] Therefore, we cannot rule out the presence of the IIA in the multinomial logit models.

To assess the robustness of our results, we also estimate binary logit models, which can be viewed as imposing the polar assumption of complete dependence[28] (Table 8). 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. By employing the equivalence tests to the simplest model, we find that three of the eleven inactive categories considered are in some sense comparable to unemployment with respect to their attachment to the labour market: the inactives who have searched for a job, the marginally-attached workers who are "waiting", and the long-term future job starters. The consideration of individual controls in a more complete model reinforces these findings, since the tests do not change significantly.

26. This modelling issue had been initially raised by Jones and Riddell (1999).

27. See the tables in Martins and Seward (2019, p. 50) for the detailed results of the Hausman and McFadden (1984) tests.

28. See Schweitzer (2003) for a similar application.

	Model with seasonal and regional controls	Model with individual controls
Subgroups of U		
U, short-term	6.415***	4.749***
	(0.101)	(0.103)
U, long-term	3.708***	2.693***
	(0.053)	(0.052)
Subgroups of M		
M, searched	3.527***▲▲	2.758***▲▲
	(0.156)	(0.128)
M, waiting	9.512***★★	7.023***★★
	(0.573)	(0.437)
M, discouraged	2.502***	2.030***
	(0.059)	(0.053)
M, personal reasons	2.221***	1.831***
	(0.061)	(0.055)
M, other reasons	2.306***	1.859***
	(0.049)	(0.050)
Subgroups of N		
N, future job starter	9.103***★★	6.591***★★
	(1.664)	(1.218)
N, student	0.753***	0.658***
	(0.013)	(0.018)
N, retired	*Excluded*	*Excluded*
N, domestic	1.343***	1.409***
	(0.023)	(0.028)
N, disabled	0.532***	0.453***
	(0.018)	(0.016)
N, other	2.213***	1.756***
	(0.055)	(0.047)
Number of observations	404,590	404,590
Pseudo-R^2	0.081	0.091

TABLE 8. Results of binary logit estimation and equivalence tests between non-employment subgroups

Source: Authors' calculations based on the Labour Force Survey (Statistics Portugal).
Notes:

1. The estimations are conducted on pooled data from the LFS for individuals occupying the non-employment group in the origin state;
2. The dependent variable takes on values 0 and 1, corresponding to two destination states: respectively, the pooled non-employment state and the employment state. Baseline category is remaining in the pooled non-employment state;
3. The reported values are the odd-ratios. The robust standard-errors are in parentheses;
4. Each model includes a constant. Seasonal and regional patterns are captured by dummy variables. The individual controls are: age, age squared, gender (male, female), marital status (single, married), education level (none, basic, secondary, higher);
5. The significance levels are: 10% (*); 5% (**); 1% (***);
6. The equivalence tests (at a 5% significance level) are: (★★) denotes coefficient statistically significantly greater relative to short-unemployed; (★) coefficient statistically significantly equal relative to short-unemployed; (▲▲) coefficient statistically significantly greater relative to long-unemployed; (▲) coefficient statistically significantly equal relative to long-unemployed.

6. Conclusion

This paper presents a perspective on the measurement of the level of slack in the Portuguese labour market, taking into acount the degree of attachment of several groups in the labour market. In this context, we provide a comprehensive assessment of the heterogeneity in the Portuguese labour market, extending the work initially developed by Centeno and Fernandes (2004) and Centeno *et al.* (2010) to the non-employed population as a whole.

By disaggregating the non-employed population into three groups (the unemployed, the marginally-attached, and the non-attached), we find an evident distinction between each of these subgroups: the unemployed are more likely to move into employment than the marginally-attached, who, in turn, move to employment with a probability roughly 10 percentage points above that of the non-attached.[29] On the basis of the statistical tests of equivalence, we conclude that the marginally-attached group constitutes a distinct state in the labour market. Moreover, marginally-attached workers display a transition behaviour closer to the unemployed than to the non-attached.

We also find significant heterogeneity among the marginally-attached. In particular, the subgroup which reports "waiting" as a reason for not having searched displays a much higher transition rate into employment, as well as a lower probability of moving to non-attachment. The performed statistical tests for the equivalence of these groups lead to a rejection of their equivalence; nevertheless, one may argue 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. Within the marginally-attached population, we also observe that those individuals who have searched for a job but are still classified as inactive[30] display a transition rate into employment which is comparable to the long-term unemployed, even after controlling for individual characteristics. In addition, we find substantial heterogeneity among the non-attached (those inactives who do not want to work). This is 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 high average transition rate into employment (36.4%). Although these individuals also frequently move to non-attachment (33.3%), their transition behaviour is closer to unemployment than to the rest of non-employed. Therefore, its classification as inactive might not be adequate.

Overall, these results suggest possible shortcomings in those analyses which use slack measures based exclusively on the job search criterion, as it is the case of the unemployment rate. A broader analysis of the labour market seems to be appropriate for an accurate assessment of the labour market slack. Nevertheless, the results indicate that the job search and the reported desire to work provide meaningful and complementary information regarding the attachment of individuals to the labour market.

29. In addition, such differences are also reflected in the reported entry wages in each of these groups.

30. Either because they have searched passively or do not fulfil the other requirements for unemployment classification.

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