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Estimating the probability of leaving unemployment for older people in Poland using survival models with censored data

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Abstract

Current demographic changes require greater participation of people aged 50 or older in the labour market. Previous research shows that the chances of returning to employment decrease with the length of the unemployment period. In the case of older people who have not reached the statutory retirement age, these chances also depend on the time they have left to retirement. Our study aims to assess the probability of leaving unemployment for people aged 50-71 based on their characteristics and the length of the unemployment period. We use data from the Labour Force Survey for 2019–2020. The key factors determining employment status are identified using the proportional hazard model. We take these factors into account and use the direct adjusted survival curve to show how the probability of returning to work in Poland changes as people age. Due to the fact that not many people take up employment around their retirement age, an in-depth evaluation of the accuracy of predictions obtained via the models is crucial to assess the results. Hence, in this paper, a time-dependent ROC curve is used. Our results indicate that the key factor that influences the return to work after an unemployment period in the case of older people in Poland is whether they reached the age of 60. Other factors that proved important in this context are the sex and the education level of older people.

Key words: employment, older workers, proportional hazard model, time-dependent ROC curve.

1. Introduction

Given the demographic changes taking place in Poland, resulting in a decrease in labour supply and an increase in the old-age dependency ratio, it is necessary to boost the participation of older people in the labour force. Understanding at the individual level the factors that favour and limit leaving unemployment for people aged 50 or more may significantly increase the effectiveness of activities related to their return to employment.

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The job-finding chances vary depending on the duration of unemployment (Sheldon, 2020; Jarosch, 2021). According to Charni (2022), the probability of returning to employment after an unemployment period decreases as workers get older. Moreover, for people aged 50 or older who do not yet have pension rights, the time remaining to obtain them is also important (Hairault et al., 2010). This study aims to assess the probability of returning to work for people aged 50–71, based on their characteristics and the length of unemployment.

The data for our study were obtained from the Labour Force Survey (LFS) from 2019–2020. Considering that not only the chances of finding a job may change over time, but also their determinants, our study focused on short-term unemployment and medium-term unemployment. Therefore, only those people who had been unemployed for a maximum of 12 months at the time of the survey were considered. The Cox regression model (Cox, 1972; Cox and Oakes, 1984) was used to identify the factors determining return to work for people aged 50–71. Then, based on this model, with the direct adjusted survival curve (Chang et al., 1982; Gail and Byar, 1986; Zhang et al., 2007) it was shown how the probability of returning to work for these people changes over time.

The use of survival models makes it possible to obtain time-dependent results, but it is associated with the analysis of censored data, which poses many challenges to the development of this class of models. The ROC curve and the area under the ROC curve (AUC) are common tools for assessing the discrimination ability of a regression model with a binary dependent variable. These methods are also used in the case of survival models, where the time-dependent ROC curve is considered (Heagerty et al., 2000; Heagerty and Zheng, 2005; Kamarudin et al., 2017). This curve is determined for various time points, which makes it possible to evaluate predictive accuracy at specific times (Guo and Jang, 2017).

The low employment rate among people aged 50 or more in Poland (Eurostat, 2022) reflects a small number of people around retirement age taking up employment. Therefore, in this paper, we focus on the predictive accuracy of the obtained results. Given that the obtained prediction changes over time, the time-dependent ROC curve was used in this study. To the best of our knowledge, this is the first study for Poland in which the probability of leaving unemployment for people aged 50 or more was estimated based on their characteristics, and predictive accuracy evaluation over time was performed.

This paper is structured as follows. The first part presents the labour force behaviour of older people in Poland and the determinants of their employment. A description of the methods used is provided in Section 3, which is followed by a description of the data (Section 4). Section 5 presents the results of our analyses. Section 6 provides a discussion and conclusive remarks.

2. The employment of people aged 50 years or older

In studies on employment of people aged 50 years or older, much attention is paid to the causes of ending their occupational careers and their withdrawal from the labour market (Gałecka-Burdziak and Góra, 2016; Jansen, 2018; Phillipson et al., 2016). Resigning from work at an older age often results in permanent withdrawal from the labour market. This is reflected, inter alia, in the differences between the statutory retirement age and the effective retirement age in Poland. In 2018, the effective retirement age in Poland was 60.6 for women and 62.8 for men (OECD, 2019), while the statutory retirement age was 60 and 65, respectively. In the same year, the employment rate for people aged from 50 to 74 years in Poland amounted to 40.2%, and by 2020 it increased by only 0.1% (Eurostat, 2022). Compared to the European average (27 countries of the European Union) of 47% in 2020, this puts Poland among the European countries where employment of older people is very low. Increasing the labour force participation of older people in Poland could, to some extent, limit the effects of population aging.

Many factors may affect the duration of the working life of people aged 50 years or older. Some factors may push these people out of the labour market, while others encourage them to stay employed. Among them, we distinguish characteristics of individuals, such as sex, age, education, skills, work experience, or place of residence, and factors directly related to the work, such as working hours, the time needed to reach a workplace, occupation, and many others. Based on Eurostat data, it can be concluded that in the case of older people, sex is the key factor affecting employment rates, in addition to age (Eurostat, 2022). Women in OECD countries, and in particular in Poland (OECD, 2019), often withdraw from the labour market much earlier than men. According to Blackburn et al. (2016), gender inequality in employment is reflected not only in the length of working life but also after retirement.

According to Rutledge et al. (2017), gender differences also occur in the chances of finding a job in the years preceding retirement. The authors indicate that the range of occupations in which employment can be found changes with age, and their availability depends on sex and education. The narrowing of the number of occupations mainly takes place at the age of 50 for less-educated men, and at the age of 60 for women and better-educated men. However, the authors make it clear that the employment opportunities for better-educated older workers have expanded significantly since the late 1990s. Also, according to Torp (2015), having a greater level of human capital in terms of education and skills may enable older people to stay active and productive for a longer time. However, Bowman et al. (2017) draw attention to the obsolescence of older workers' job skills, which is a significant problem limiting employment opportunities in older age. Moreover, the authors argue that the competitiveness of older workers in the labour market is not only a function of their knowledge and technical job skills. Consequently, competencies currently desired in the labour market cannot be acquired through investments made by an individual.

According to the results of a study by Charni (2022) based on British panel data, the age of employees has a large impact on their chances of getting back to work after unemployment, in addition to human capital characteristics and economic incentives. Older jobseekers are longer unemployed than younger jobseekers (Bowman et al., 2017). According to Charni (2022), the time it takes for older people to return to employment after an unemployment spell would be shorter if they were treated in the same way as younger people. This result indicates the need to combat age discrimination also in the workplace and when looking for employees. According to Fleischmann et al. (2015), the treatment of older workers is influenced not only by the characteristics of the organization but most of all by the local labour market. A significant drop in labour supply may significantly impact how older workers are perceived by employers in Poland.

3. Methods

In the survival analysis, the most popular basic function is the survival function:

$$S(t) = P(T > t), \tag{1}$$

where T is the variable describing the time until the event occurs. The Kaplan-Meier method (Kaplan and Meier, 1958) or the Nelson-Aalen method (Aalen, 1978; Nelson, 1972) are most often used to estimate this function. An alternative to these methods is the Cox regression model approach (Cox, 1972; Cox and Oakes, 1984):

$$h(t) = h_0(t)\exp(\mathbf{x}'\boldsymbol{\beta}). \tag{2}$$

In the proportional hazard model, the formula for the survival function is given as follows:

$$S(t) = [S_0(t)]^{\exp(\mathbf{x}'\boldsymbol{\beta})}, \tag{3}$$

where $\boldsymbol{\beta}$ is a vector of estimated model parameters, and $S_0(t)$ is a baseline survival function corresponding to a baseline hazard $h_0(t)$. The baseline survival function S_0 can be written using the cumulative hazard function H_0 as follows:

$$S_0(t) = \exp\bigl(-H_0(t)\bigr), \tag{4}$$

where $H_0(t) = \int_0^t h_0(u)\,du$, $t \geq 0$. The estimator of the survival function $S(t)$ can be written in the following form:

$$\hat{S}(t) = \bigl[\hat{S}_0(t)\bigr]^{\exp(\mathbf{x}'\hat{\boldsymbol{\beta}})}, \tag{5}$$

where $\widehat{\boldsymbol{\beta}}$ denotes the estimator of the parameter vector $\boldsymbol{\beta}$, and $\hat{S}_0$ is an estimator of a baseline survival function, which is given by the following formula:

$$\hat{S}_0(t) = \prod_{u|t_{(u)}<t}\left(1 - \frac{d_u}{\sum_{l\in R\left(t_{(u)}\right)} \exp(\mathbf{x}_l'\widehat{\boldsymbol{\beta}})}\right), \tag{6}$$

where d_u, $u = 1,2,\dots,m$ is the number of observations, for which the event occurred at time $t_{(u)}$, $u = 1,2,\dots,m$, and $R\left(t_{(u)}\right)$, $u = 1,2,\dots,m$, denotes a hazard set. The hazard set includes all individuals for which the survival or censoring time is greater than $t_{(u)}$.

Let j denote an individual belonging to the k-th group, then the observed values for this individual can be described by $\{t_{kj}, v_{kj}, \mathbf{x}_{kj}\}$, $k = 1,2,\dots,K, j = 1,2,\dots,n_k$, where t_{kj} is the observed time, v_{kj} =0, when censoring occurs and v_{kj} =1, otherwise, and $\mathbf{x}_{kj}$ denotes a covariates vector. Then, the survival function at time point t, for an individual from the k-th group, with values of variables $\mathbf{x}$, is given by the formula (Chang et al., 1982; Gail and Byar, 1986; Zhang et al., 2007):

$$\hat{S}_k(t;\mathbf{x}) = \exp\{-\widehat{H}_{0k}(t)\exp(\mathbf{x}'\widehat{\boldsymbol{\beta}})\}. \tag{7}$$

Then, the general formula for the direct adjusted survival function estimator has the following form:

$$\hat{S}_k(t) = \frac{1}{n}\sum_{l=1}^{n}\exp\{-\widehat{H}_{0k}(t)\exp(\mathbf{x}_l'\widehat{\boldsymbol{\beta}})\}, \tag{8}$$

where $n = \sum_{k=1}^{K} n_k$.

The Cox regression results can also be used to obtain estimates of a time-dependent sensitivity and a time-dependent specificity, and in consequence to obtain estimates of the time-dependent ROC curve (Heagerty et al., 2000; Heagerty and Zheng, 2005).

Let T denote a variable describing the time until the event occurs, and $Z_i = \mathbf{x}_i'\boldsymbol{\beta}$ for i-th individual ($i = 1,2,\dots,n$). Moreover, let $D_i(t)$ denote status of i-th individual at time t defined as follows:

$$\mathrm{D}_i(t) = I(T \le t). \tag{9}$$

Then, for a given cut-off point c, the time-dependent sensitivity (Se) and the time-dependent specificity (Sp) can be defined as follows (Heagerty et al., 2000; Heagerty and Zheng, 2005; Kamarudin et al., 2017):

$$Se(c,t) = P(Z_i > c|D_i(t) = 1), \tag{10}$$

$$Sp(c,t) = P(Z_i \le c|D_i(t) = 0). \tag{11}$$

Let TPR (True Positive Rate) be given by the formula $TPR(c,t) = Se(c,t)$, and FPR (False Positive Rate) will be calculated as follows: $FPR(c,t) = 1 - TNR(c,t) = 1 - Sp(c,t)$, where TNR denotes True Negative Rate. Thus, the time-dependent ROC curve (ROC) can be determined for any time points t and for varying cut-off points c as follows:

$$ROC(t) = \{(FPR(c,t), TPR(c,t)) : c \in \mathbf{R}\}. \quad (12)$$

Then, the time-dependent AUC is defined as follows:

$$AUC(t) = \int_{-\infty}^{+\infty} Se(c,t) d[1 - Sp(c,t)]. \quad (13)$$

4. Data

The estimation of the probability of returning to work for people aged 50-71 was made based on the data from the LFS for Poland for 2019 and 2020. The study included people who during the first wave of the survey conducted in 2019 answered both the question “During the week in question, Monday through Sunday, did you do any work for at least one hour that generated income or earnings, or did you assist on an unpaid basis in a family business?”, and the question "Did you have a job in the surveyed week, but did not perform it temporarily?" with “no”. Short-term and medium-term unemployment was studied, therefore only those who had stopped working no more than 12 months before the first wave of the survey was performed in 2019 were included in the study. As many as 619 people were identified, and only 5.33% of them took up employment in the analysed period. For the survival analysis, it was assumed that an event occurred for these people.

The time was calculated in months from the moment of leaving the last job until the beginning of work or until the end of the observation period, i.e. the moment of the last wave of the survey in which the respondent participated. The observation time ranged from 1 month to 27 months. When constructing the variable describing the age of a respondent, the different retirement ages for women and men in Poland were considered. This variable was defined in such a way as to determine those who have not yet retired. The set of other individual characteristics included in the study is presented in Table 1. Due to a small share of people from the central macroregion and difficulties in estimating appropriate coefficients for the needs of the analysis, the central macroregion was combined with the southwestern macroregion.

Table 1: Sample characteristics

Variable	Categories	Percent
Sex	Men	46.20
	Women	53.80
Age	50–54 years old	8.72
	55–60 years old	22.29
	61–65 years old	48.47
	66–71 years old	20.52

Table 1: Sample characteristics (cont.)

Variable	Categories	Percent
Marital status	Single	22.78
	Married	77.22
Educational level	Higher	15.02
	Post-secondary or secondary professional or secondary general	31.34
	Basic vocational	33.93
	Primary school	19.71
Last job type	Self-employed	12.92
	Other	87.08
Employment sector - last job	Public	29.89
	Private	70.11
Place of residence	City 100,000 residents or more	33.12
	City from 20,000 to 100,000 residents	21.16
	City under 20,000 residents	15.83
	Rural areas	29.89
Macroregion	Southern (Regions: małopolskie, śląskie)	13.41
	North-Western (Regions: wielkopolskie, zachodniopomorskie, lubuskie)	19.06
	South-Western (Regions: dolnośląskie, opolskie)	11.79
	Northern (Regions: kujawsko-pomorskie, warmińsko-mazurskie, pomorskie)	17.61
	Central (Regions: łódzkie, świętokrzyskie)	8.08
	Eastern (Regions: lubelskie, podkarpackie, podlaskie)	17.13
	Mazovian Province (Regions: warszawski stołeczny, mazowiecki regionalny)	12.92
Were you looking for a job in the last 4 weeks?	Yes	9.21
	No, because I already have a job and I am waiting for it to start	1.78
	No	89.01

Source: *Own calculations; data from Labour Force Survey 2019 and 2020, Poland.*

5. Results

In the first stage of this research, the factors influencing the employment of people aged 50-71 were identified with the proportional hazard model. The use of this model required prior verification of the assumed hazard proportionality. For this purpose, time-dependent variables were incorporated into the model. We found out that this assumption is fulfilled for all considered variables. The estimates of the proportional hazards model parameters are presented in Table 2.

It was found that men had over two times greater hazard of taking up employment than women. However, the key factors that affected the employment of respondents were their age and educational level. People aged 50–54 had an 8.37 times greater hazard of taking up employment than people aged 66–71. A similar result was obtained for people aged 55–60, they had a 7.28 times greater hazard of taking up employment compared to the oldest people. In the case of people aged 61-65, no statistically significant differences were observed compared to the oldest people. People with a high level of education had a 12.91 times greater hazard of taking up employment than people with primary education. People with post-secondary or secondary professional or secondary general education had a 10.92 times greater hazard of taking up employment compared to people with primary education. People with vocational education had a 6.9 times greater hazard of taking up employment compared to the least-educated people. People who had worked in the public sector in their last job had a 67.5% lower hazard of taking up employment, compared to people who had worked in the private sector in their last job. In the case of the variable describing the type of place of residence, only one level turned out to be statistically significant. People who lived in cities of under 20,000 residents had a 2.6 times greater hazard of taking up employment than people who had lived in rural areas. The remaining levels of the variable describing the type of place of the residence turned out to be statistically insignificant. Moreover, in the model, we included two control variables: a variable describing the macroregion of residence and information if the respondent was looking for a job in the last 4 weeks.

Table 2: Estimated parameters, standard error, *p*-value, and hazard ratio – results from the proportional hazards model

Covariate	Parameter estimate	Standard error	*p*-value	Hazard ratio
Sex (*ref. Women*)				
Men	0.8130	0.4180	0.0518	2.255
Age (*ref. 66–71 years*)				
50–54 years old	2.1245	0.9778	0.0298	8.369
55–60 years old	1.9856	0.9297	0.0327	7.283
61–65 years old	0.1663	0.9735	0.8644	1.181
Educational level (*ref. Primary school*)				
Higher	2.5581	1.0248	0.0126	12.912
Post-secondary or secondary professional or secondary general	2.3904	0.8854	0.0069	10.917
Basic vocational	1.9312	0.8603	0.0248	6.898

Table 2: Estimated parameters, standard error, *p*-value, and hazard ratio – results from the proportional hazards model (cont.)

Covariate	Parameter estimate	Standard error	p-value	Hazard ratio
Employment sector - last job (*ref. Private*)				
Public	-1.1225	0.6573	0.0877	0.325
Place of residence (*ref. Rural areas*)				
City 100,000 residents and more	0.0511	0.5318	0.9235	1.052
City from 20,000 to 100,000 residents	-0.2432	0.5141	0.6361	0.784
City under 20,000 residents	0.9582	0.5518	0.0824	2.607
Macroregion - Mazovian Province (*ref. Regions: warszawski stołeczny, mazowiecki regionalny)*				
Southern Macroregion (małopolskie, śląskie)	1.3110	0.7512	0.0809	3.710
North-Western Macroregion (wielkopolskie, zachodniopomorskie, lubuskie)	1.1785	0.7363	0.1095	3.250
South-Western Macroregion (dolnośląskie, opolskie) and centralny (łódzkie, świętokrzyskie)	-1.4186	1.0018	0.1567	0.242
Northern Macroregion (kujawsko-pomorskie, warmińsko-mazurskie, pomorskie)	1.7406	0.7157	0.0150	5.701
Eastern Macroregion (lubelskie, podkarpackie, podlaskie)	1.3310	0.7512	0.0764	3.785
Were you looking for a job in the last 4 weeks? (*ref. No)*				
Yes	1.9524	0.4496	<.0001	7.045
No, because I already have a job and I am waiting for it to start	3.6336	0.7051	<.0001	37.849

Source: Own calculations; data from Labour Force Survey 2019 and 2020, Poland.

Based on Cox regression with the direct adjusted survival curve, it was shown how the probability of returning to work for respondents changes over survey time. It was found that this probability increased very slowly, and it did not even exceed the value of 0.1 (Figure 1).

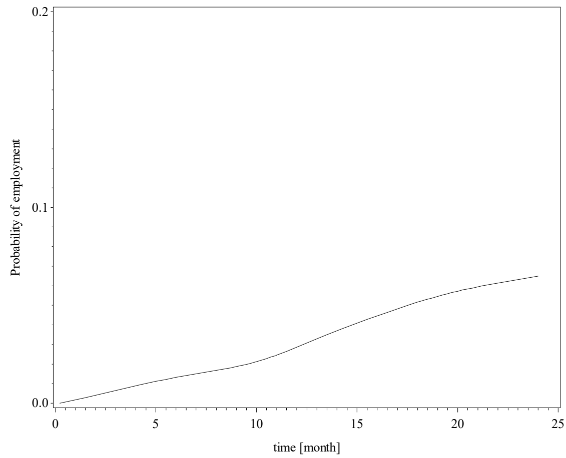


Figure 1: The probability of leaving unemployment for all individuals determined with the direct adjusted survival curves

Due to the different retirement ages for women and men in Poland, the direct adjusted survival curve was estimated in the groups determined by sex. It was found that after about 10 months the probability of taking up employment increased for both women and men, but in the case of men this increase was higher (Figure 2). In the next stage of this research, the direct adjusted survival curve was estimated in the groups defined by the age of the respondents. It was found that in the analysed period the probability of leaving unemployment for people aged 50–54 is very similar to the probability of leaving unemployment for people aged 55–60.

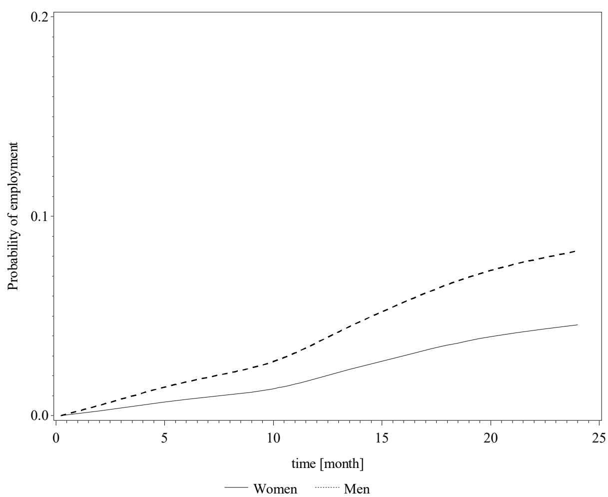


Figure 2: The probability of leaving unemployment for women and men determined with the direct adjusted survival curves

The similarity was observed for people aged 61–65 and people aged 66–71 too (Figure 3). People aged 50–54 and 55–60 had a greater probability of taking up employment than older people. This probability started to increase after 10 months but ultimately did not exceed the value of 0.2. In the case of people aged 61–65 and 66–70, the increase in the probability of taking up employment was very small – the probability of taking up employment remained at a very low level throughout the entire period under study.

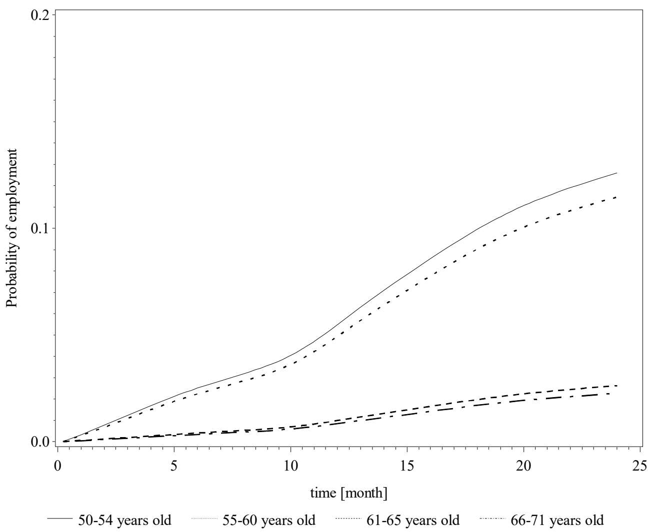


Figure 3: The probability of taking up employment by age determined with the direct adjusted survival curves

Among the surveyed respondents, only 5.33% took up employment in the period under study. Due to such a small percentage of events, the evaluation of predictive accuracy was performed. For this purpose, time-dependent ROC curves were used. Based on the obtained results, it can be concluded that our prediction is better than the random one over the whole analysed period (Figure 4). Moreover, the predictive accuracy increases with time, starting from the 5th month. Additionally, Figures 5–8 show the shape of ROC curves at selected time points (after 6, 12, 18, and 24 months). The shapes of the time-dependent ROC curves confirm the high quality of the previously presented probability estimates for leaving unemployment for the surveyed respondents aged 50 years or older. The AUC at 6 months was 0.764, at 12 months was 0.836, at 18 months 0.841, and at 24 months it reached 0.874.

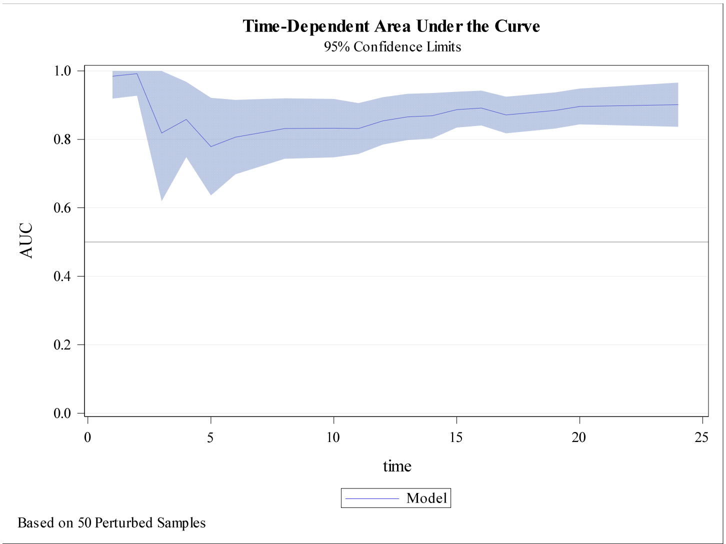
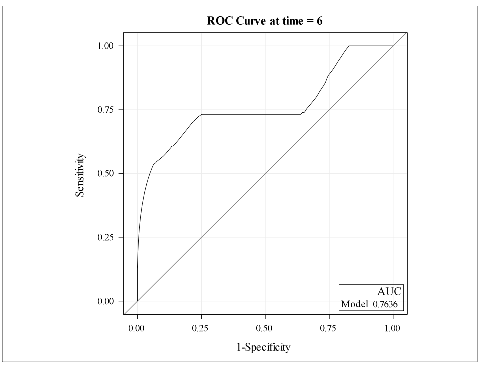


Figure 4: The time-dependent area under the ROC curve and the 95% confidence limits



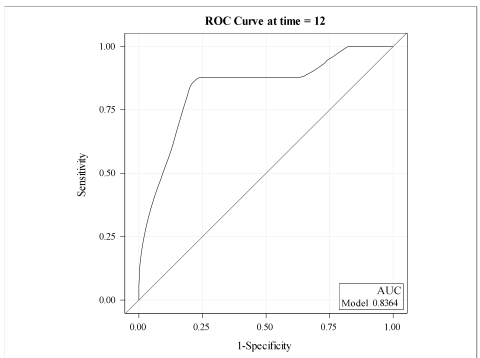


Figure 5: ROC curve at 6 months

Figure 6: ROC curve at 12 months

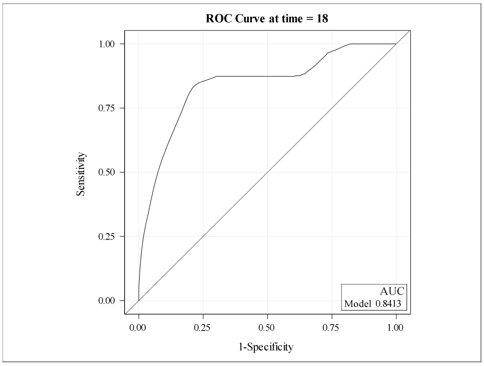


Figure 7: ROC curve at 18 months

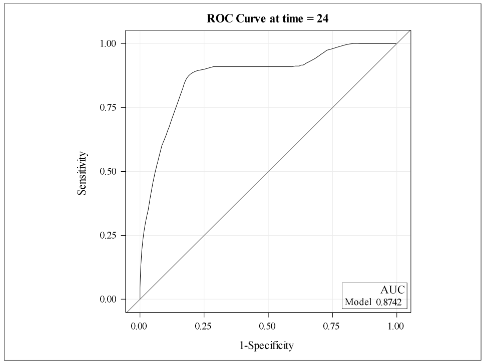


Figure 8: ROC curve at 24 months

6. Discussion and conclusion

A further increase in the demographic dependency ratio may pose a threat to the stability of the pension system in Poland. Therefore, it is necessary to take measures that would effectively encourage the elderly to stay longer in the labour market, even after reaching retirement age. This study raises the issue of returning to work after a break in employment by people aged 50 years or older in Poland. Moreover, prolonged unemployment of people in the pre-retirement age may cause permanent withdrawal from the labour market.

In the first stage of the research, the factors determining return to work for people aged 50–71 were identified with the proportional hazards model. It was found that the age of the respondents had a large impact on taking up employment. People who had not yet reached the statutory retirement age for women in Poland (60 years) had over seven times greater hazard of taking up employment than those aged 66–71. However, no statistically significant differences were found between people aged 61–65 and people aged 66–71. This result is similar to the results of previous studies based on data from other countries indicating the major importance of age in the case of older people in returning to employment after an unemployment spell (Bowman et al., 2017; Charni, 2022). Moreover, we showed the large impact of reaching the statutory retirement age on taking up employment after a break in employment for the surveyed respondents.

The other key factors that affected the return to employment of people aged 50–71 after an unemployment spell were sex and educational level. We revealed that men had over two times more chances of employment than women. This result is in line with previous research results for other countries (Blackburn et al., 2016; Rutledge et al., 2017). However, taking into account the result obtained for Poland and the 16.6% difference (Eurostat, 2022) in the value of employment rate for women and men aged 50 to 74 in 2020 in Poland this problem seems to particularly affect the Polish labour market. Moreover, our research indicates that also the level of education was relevant for leaving unemployment for people aged 50–71. The previous study based on US data (Rutledge et al., 2017) also indicates such a relationship. In addition, according to Batyra et al. (2019), low-skilled senior workers demonstrate a higher probability of not only unemployment but also of early withdrawal from the labour market.

The results of the second part of our research revealed that the probability of leaving unemployment for respondents aged 50–71 in the period under consideration increased very slowly over time, and ultimately did not even exceed the value of 0.1. Looking at our result as well as earlier findings of Charni (2022) it can be concluded that only a few unemployed people who are around retirement age return to work after an unemployment spell. Moreover, we showed how the probability of taking up employment changes over time depending on sex. It was found that after 10 months the probability of taking up employment increases for both women and men, but in the case of men this increase is slightly higher. The analysis of the probability of taking up employment depending on age confirmed the earlier conclusions that the key time point followed by a decline in the chances of returning to work is reached at the age of 61. In addition, we have shown the relationship between returning to work and the period during which unemployment benefits were paid, which is usually 6 or 12 months. After about 10 months, the probability of taking up employment increased, albeit slightly, for all analysed groups of respondents.

The time-dependent ROC curve analyses allow the conclusion that obtained predictive accuracy increases with time and is at a satisfactory level during the entire period under observation (after 24 months the AUC reached the value of 0.874).

Based on our results, it can be concluded that it is crucial to take actions that will promote the continuity of employment of people in the pre-retirement age in Poland because any return to employment after an unemployment spell is very unlikely for people aged 50 years or older.

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