

Analysis of the Impact of Innovative Economic Conditions on the Flow of Workers in the Labour Markets of the European Union Countries

Grażyna Węgrzyn  <https://orcid.org/0000-0003-4735-2807>

Associate Professor, Wrocław University of Economics and Business, Wrocław, Poland
e-mail: grazyna.wegrzyn@ue.wroc.pl

Marcin Salamaga  <https://orcid.org/0000-0003-0225-6651>

Associate Professor, Cracow University of Economics, Kraków, Poland, e-mail: salamaga@uek.krakow.pl

Abstract

The main purpose of the work is to present the results of empirical research on the impact of innovation levels in the economy on the structure of labour market flows. The analysis of the directions and scale of these flows makes it possible to discover important characteristics of the labour market and thus makes it possible to better construct and target policies to reduce unemployment or activate economically inactive people. The study uses data from the Labour Force Survey (LFS) and experimental job-to-job statistics for the European Union (EU) countries, covering the 2011–2019 period. We conducted research separately for selected groups of economies classified by their level of innovation, i.e. Innovation Leaders, Strong Innovators, Moderate Innovators, and Emerging Innovators. The results demonstrate that the structure of flows in a labour market depends on the innovation level of the respective economy. The main contribution of the study is that it identifies employee flow patterns in the labour markets of individual EU countries from the perspective of the innovation levels of their respective economies. Panel error correction models (ECM) and panel causality tests were used. In countries that are Innovation Leaders, an increase in participation in lifelong learning leads to a parallel increase in employee flow (EE) and job-to-job employee turnover. In countries that are Emerging Innovators, increasing participation in lifelong learning increases turnover, mainly among young people (15–24 age group).



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Received: 16.08.2022. Verified: 14.02.2023. Accepted: 15.06.2023

Keywords: labour market flow, transitions in labour market status, job-to-job, innovation economy

JEL: J21, O30

Introduction

The increase in economic innovativeness is widely recognised as the key driving force behind the transformative changes occurring in societies. The ongoing changes strongly affect the labour market as they change the rules of how it functions and the ways people perform work. Identifying what is happening in the labour market is essential for designing and implementing active labour market policies. To identify the adjustments taking place in the labour market in full detail, we will use stream analyses that allow for dynamic analysis. Analysing flows involves studying the shifts in individuals' labour market activity across the three primary states of economic activity: employment (E), unemployment (U), and economic inactivity (I). This analysis enables a thorough evaluation of the actual transitions between these states and provides estimates for the probable transitions between them. Thus, it helps to understand and interpret changes in labour market indicators. Labour flows and transition rates underlie the latest unemployment models, based on Mortensen-Pissarides' search-and-matching theory (Mortensen and Pissarides 1994), especially in markets with search frictions. A thorough analysis of flows is essential not only for a scientific description and understanding of the economic reality, but also for rational public intervention in the labour market.

The subject literature includes papers that present the results of research on the impact of the general economic situation and labour markets' flexibility on the dynamics and structure of flows in the labour market. It is assumed that employee flows result mainly from demand-vs.-supply factors (Davis, Faberman, and Haltiwanger 2006, pp. 3–26). The research carried out so far focused on changes in labour market flows that result from the general economic situation (Blanchard and Diamond 1990, pp. 85–143; Fujita and Nakajima 2013), from wage levels (Moscarini and Postel-Vinay 2017, pp. 364–368), from labour market flexibility (Elsby, Hobijn, and Sahin 2011), and from institutional changes (Cournède, Denk, and Garda 2016).

As the results are ambiguous and do not fully explain the labour market changes, this study attempts to obtain more complete knowledge of the adjustments taking place there. Understanding the economic facet of these phenomena is crucial not only for the scientific description of economic reality, but also for planning and optimal public intervention. The international variation of the scale of flows in the labour market is the springboard for the considerations presented in this paper, which focus on the innovation levels of individual economies and their impact on the flows of people in the national labour market. The analysis was conducted separately for four groups

of countries that were distinguished by their respective levels of innovation as measured with the European Innovation Scoreboard (EIS), i.e. Innovation Leaders, Strong Innovators, Moderate Innovators, and Emerging Innovators.

The main purpose of the work is to present the results of empirical research on the impact of the level of innovation in the economy on the structure of flows in the labour market. The main contribution of the study is that it identifies flow patterns in the labour markets of individual European Union (EU) countries from the perspective of the levels of innovation of their respective economies. We demonstrate how the scale and direction of employee flows in the labour market are determined by the economy's level of innovation. Consequently, understanding the structure and direction of workers' flows between individual statuses of economic activity allows us to identify flow patterns in the labour market.

Empirical regularities regarding the flows of labour

Flows of people in the labour market between the three statuses (i.e. employment, unemployment and economic inactivity) depend on the economic cycle. It is one of the issues most frequently described in the literature on labour market flows (Fujita and Nakajima 2013). Most of the published results show that flows from employment to unemployment are countercyclical, while the flows from unemployment to employment are procyclical (Shimer 2010). Research conducted in the wake of the 2008–2009 economic crisis confirmed that employment is characterised by high, procyclical volatility within the economic cycle. Using 1993–2010 quarterly data from the Labour Force Survey for Great Britain, Gomez (2012, pp. 165–175) showed that “every quarter, 6% of all employees are searching for a different job. Job-to-job transition probability is strongly procyclical, but the number of employees searching for a different job is countercyclical.” In the United States, however, the rate of people employed but seeking another job was twice as high, at 15%. Balmaseda, Dolado and Lopez-Salido (2000, pp. 3–23) indicate that the type of economic shock is responsible for the cyclical volatility of employment. The dominant role of the negative demand shock caused by the financial crisis of 2008–2009 was of great importance for both the course of the adjustments in the labour market and for the direction of the economic policies pursued.

The existing analysis of theoretical approaches and results of empirical research also indicates that adjustment mechanisms in the labour market are determined by the character of the labour market institutions in individual countries (Blanchard 2005; Cournède et al. 2016; Boeri and van Ours 2021). Labour market institutions, which create a system of norms, incentives and restrictions for the behaviour of labour market actors, influence the economic decisions made by these actors and, consequently, they af-

fect the scale of the labour market's quantitative (in the form of employment changes) and qualitative adjustments to economic shocks (Boeri and van Ours 2021).

The institutional environment of the labour market affects the adjustments that follow economic shocks, and institutional differences are considered the key source of variations in individual countries (Bassanini and Duval 2006). In the subject literature, the labour market's capability to adapt to changing conditions is most often referred to as "flexibility". In macroeconomic terms, labour market flexibility means the ability to recover from economic shocks. Countries with rigid labour markets are characterised by a low probability of people moving between different statuses in the labour market. The existence of restrictions on employee dismissal induces companies to reduce employment as the expected cost of future layoffs increases. The same refers to the cost of adjusting the size of the workforce to changing conditions and needs (Mortensen and Pissarides 1994, pp. 397–415). This is in line with studies that demonstrated that overly restrictive provisions on permanent employment contracts reduce flows to employment (Haltiwanger, Scarpetta, and Schweiger 2013, pp. 11–25). However, Cournède, Denk, and Garda (2016) arrived at different conclusions. They did not find a significant long-term impact of labour market regulations on the probability of transitioning between particular statuses in the labour market. This applies especially to employees with low income and poor qualifications, whose situation does not depend on labour market flexibility but on the quality of vocational activation programs.

Research by Pieroni and Pompei (2008, pp. 325–347) on the Italian economy showed that higher employee turnover negatively affects the innovative activity of enterprises in technologically advanced regions, while the impact is positive in regions with a low level of technological advancement. Increased staff turnover in the traditional sectors of the economy enhances the flows of knowledge and contributes to the intensity of innovative activities.

The analysis of changes in individuals' past statuses in the labour market makes it possible to predict the differentiation of their future positions in this market (i.e. the probability of retaining or changing a given status). Understanding the structure of flows between individual statuses of economic activity allows inferences about the probability of starting (or maintaining) employment, the level of unemployment risk or the tendency for economic deactivation in the population groups identified by specific characteristics (Socha and Sztanderska 2002).

Data and methods

The study makes use of secondary data from the Eurostat database. The spatial scope of the research covers the EU area, i.e. the 27 European countries, divided into four groups by their level of innovation as measured by the Summary Innovation Index (SII), i.e., Innovation Leaders, Strong Innovators, Moderate Innovators, and Emerging Innovators. The SII indicator is based on Community Innovation Surveys (CIS) data and published annually as the European Innovation Scoreboard (*European Innovation Scoreboard 2021* 2021). Many authors use the SII indicator to assess economies' levels of innovation (Janoskova and Kral 2019, pp. 68–83). Data on flows between the employed, unemployed and inactive statuses come from the Labour Force Survey. As the statistics on labour market flows do not capture people who have not changed their status in the labour market, the study additionally includes data on job-to-job rotation. The time range of the data covers 2011–2019.

Correlation analysis was used to make a preliminary assessment of the impact of innovation indicators on the flows in the national labour markets within the EU. In the core research on the relationship between labour market flows and innovation indicators, panel error correction models (ECM) were used. These types of tools, as well as other macroeconomic variables, were also applied in studies on the relationship between the national levels of innovation and direct foreign investment (Akbas, Senturk, and Sancar 2013, pp. 791–812; Erdala and Göçer 2015, pp. 749–758). However, in research on employee flows in the labour market and innovation, no such methods have been used in the available scientific publications. Therefore, the methodological approach used in our study of the relationship between innovation indicators and employee flows in the European labour markets should be considered innovative.

The panel ECM combines the econometric tools from dynamic time series analysis with panel data analysis. The use of this approach was determined by the nature of the data, the need to take into account the impact of historical values of variables (autoregressive processes) on their current values, and the intent to identify a long-run relationship between the labour market indicators and the innovativeness of enterprises. The proposed approach makes it possible to determine a time-independent equilibrium path for cointegrated economic processes along with short-term deviations from this state of equilibrium. This research methodology requires examining the existence of a unit root of the respective time series (Baltagi and Kao 2000, pp. 7–52).

A key element in modelling long-term relationships is to investigate the existence of the following cointegrating relationship:

$$\ln y_{its} = \beta_{i0} + \sum_{j=1}^4 \beta_{ij} \ln X_{ij} + u_{it}, \quad (1)$$

where:

y_{its} – s -th dependent variable in the i -th cross-section (here: country) in period t ,
 X_{ij} – j -th explanatory variable in the i -th cross-section (here: country) in period t ,
 u_{it} – random error terms which are uncorrelated white noise processes.

The following y_s dependent variables were proposed:

y_1 – transition employment–employment (EE),
 y_2 – transition employment–unemployment (EU),
 y_3 – transition employment–inactivity (EI),
 y_4 – transition unemployment–employment (UE),
 y_5 – transition inactive–employment (IE),
 y_6 – employee “job-to-job” turnover in the 15–24 age group (JJ_1),
 y_7 – employee “job-to-job” turnover in the 15–74 age group (JJ_2).

The following explanatory variables X_j were used in the models:

X_1 – percentage of the population aged 25–34 with tertiary education,
 X_2 – percentage of the population aged 25–64 involved in lifelong learning,
 X_3 – enterprises that provide training to develop or upgrade their personnel’s ICT skills,
 X_4 – employment in knowledge-intensive activities (% of total employment).

For stationary variables, it is possible to build ECM models and thus estimate short-term relationships. The single-equation model of error correction for stationary variable increments used when analysing short-term relationships for panel data can be written as follows:

$$\Delta y_{it} = \alpha_0 + \sum_{j=1}^p \alpha_{1j} \Delta y_{i,t-j} + \sum_{j=1}^q \alpha_{2j} \Delta x_{i,t-j} + \gamma ECT_{i,t-1} + \varepsilon_{it}, \quad (2)$$

where:

$ECT_{i,t-1}$ – error-correction term representing the long-term relationship,
 p, q – orders of lagged differences in variables (selected using the Schwarz information criterion),
 ε_{it} – standard error of the model.

The stationary nature of the time series was ensured by considering logarithmic variables in the models and calculating their first increments. The stationary nature of the time series of logarithmic variables was investigated using panel tests of the unit root – Fish-

er type (PP) and Breitung unit root test (Breitung 2000, pp. 161–178). In the investigation of time series cointegration, the panel tests of Pedroni (1999, pp. 653–670) and Kao (1999, pp. 1–44) were used.

The test results confirmed cointegration in the time series. Therefore, the fully modified ordinary least squares (FMOLS – *Fully Modified Least Squares*) method was used to estimate long-term relationships between seven explanatory variables according to Model 1. The analysis was conducted separately for groups of Innovation Leaders, Strong Innovators, Moderate Innovators and Emerging Innovators.

Results

Countries were grouped in terms of innovation level according to the European Innovation Scoreboard 2021:

- Innovation Leaders: Belgium, Denmark, Finland, and Sweden.
- Strong Innovators: Austria, Estonia, France, Germany, Ireland, Luxembourg, and the Netherlands.
- Moderate Innovators: Cyprus, Czechia, Greece, Italy, Lithuania, Malta, Portugal, Slovenia, and Spain.
- Emerging Innovators: Bulgaria, Croatia, Hungary, Latvia, Poland, Romania, and Slovakia.

Tables 1–4 present the results of estimating long-term correlation models that show the impact of the X_1 – X_4 variables on employee flows and turnovers in the four groups of EU countries.

The data in Table 1 show that among the Innovation Leader countries, a long-term increase in the value of the X_1 variable (the percentage of the population aged 25–34 with tertiary education) simultaneously causes a significant (significance level – 0.05) decrease in EI flows, but a significant increase in all EE flows and in the employee rotation JJ_1 and JJ_2, at the same level of significance, *ceteris paribus*. An increase in the X_2 variable (the percentage of the population aged 25–64 involved in lifelong learning) significantly decreases IE employee flows (significance level – 0.01) and the volume of EI and EU employee flows (significance level – 0.05) while increasing the volume of EE flows and both JJ turnovers (significance level – 0.01), *ceteris paribus*. An increase in the X_3 variable (enterprises that provide training to develop or upgrade their personnel’s ICT skills) decreases EE employee flows (significance level – 0.05) and JJ_2 employee turnover (significance level – 0.01), *ceteris paribus*.

A long-term increase in the X_4 variable (employment in knowledge-intensive activities (% of total employment)) significantly increases (significance level – 0.01) EE flows and both JJ employee turnovers, ceteris paribus. Moreover, an increase in this variable at the significance level of 0.05 leads to a significant decrease in the value of other flows, ceteris paribus.

Table 1. Evaluation of long-term relationship parameters in models estimated with the FMOLS estimator for the group of countries classified as Innovation Leaders (data from 2011–2019)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
const	β_0	2.022 (2.036)	22.024 (15.165)	15.224 (16.217)	15.762 (6.742)	-20.022 (26.227)	5.156 (4.158)	-8.054 (7.884)
lnX ₁	β_1	0.221*** (0.072)	-5.270 (8.493)	-2.771** (1.152)	5.057* (2.722)	4.447 (9.224)	0.367*** (0.105)	6.014*** (1.805)
lnX ₂	β_2	0.075*** (0.020)	-1.160* (0.653)	-0.507** (0.227)	-0.771** (0.279)	-0.711*** (0.026)	0.247*** (0.023)	0.839*** (0.271)
lnX ₃	β_3	-0.016** (0.009)	-0.067 (0.432)	0.212 (0.149)	-0.229 (0.346)	0.296 (0.220)	-0.052 (0.069)	-0.456*** (0.104)
lnX ₄	β_4	0.219*** (0.012)	-5.541** (2.477)	-1.927** (0.795)	-2.972** (1.172)	-2.726** (0.979)	0.468*** (0.084)	3.681*** (0.643)
R ²		69.863%	62.23%	83.18%	76.24%	80.22%	75.23%	78.63%

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *
 Source: own calculations based on Eurostat n.d.

Table 2. Evaluation of long-term relationship parameters in models estimated with the FMOLS estimator for the group of countries classified as Strong Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
const	β_0	3.338*** (0.125)	33.381*** (6.050)	-0.258 (1.712)	5.070*** (1.738)	-2.837* (1.511)	6.050*** (1.542)	5.411*** (1.128)
lnX ₁	β_1	0.050 (0.053)	6.125*** (1.631)	-0.238*** (0.061)	-0.373*** (0.071)	-0.371*** (0.007)	-0.576*** (0.048)	-0.491*** (0.052)
lnX ₂	β_2	-0.260*** (0.020)	5.682*** (0.851)	0.828*** (0.268)	0.685** (0.274)	-1.023*** (0.237)	0.725*** (0.169)	0.682 (0.548)
lnX ₃	β_3	0.025** (0.011)	-0.173 (0.511)	0.120** (0.033)	0.018 (0.238)	0.035 (0.127)	-0.025*** (0.008)	-0.065 (0.057)
lnX ₄	β_4	-0.036 (0.033)	-8.263*** (1.622)	-0.158 (0.358)	-0.882*** (0.068)	-0.332*** (0.004)	-0.492*** (0.071)	-0.547*** (0.068)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
R ²		84.54%	66.28%	74.52%	71.46%	82.32%	85.27%	78.47%

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *

Source: own calculations based on Eurostat n.d.

The data in Table 2 show that among the Strong Innovator countries, in the long term, the increase in the X_1 variable (the percentage of the population aged 25–34 with tertiary education) causes a significant (significance level – 0.01) increase in EU flows and a significant decrease in the EI, UE, IE, JJ_1 and JJ_2 variables. For example, a one-per-cent increase in the *percentage of the population aged 25–34 with tertiary education* increases the flow of EU workers by an average of approx. 6.125%, ceteris paribus. At the same time, it reduces EI flows by an average of approx. 0.238%, ceteris paribus. It can thus be concluded that an increase in the X_2 variable (*the percentage of the population aged 25–64 involved in lifelong learning*) causes a significant increase (significance level – 0.01) in EU, EI, EU, and JJ_1 flows, but a significant reduction in the EE and IE flows (ceteris paribus). A positive and significant impact (significance level – 0.05) of the X_3 variable (*enterprises that training to develop or upgrade their personnel's ICT skills*) is visible in the EE and IE variables, and a negative one (significance level – 0.01) in the JJ_1 turnover (in the other variables representing the flows/turnovers in the labour market, no significant impact of the X_3 variable was found). An increase in the value of the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) in the long term significantly (significance level – 0.01) reduces the EU, EU, IE flows of employees and the turnovers of JJ_1 and JJ_2, ceteris paribus.

Table 3. Evaluation of long-term relationship parameters in models estimated with the FMOLS estimator for the group of countries classified as Moderate Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
const	β_0	4.510*** (0.061)	1.152*** (0.090)	2.215*** (0.654)	-0.202 (0.622)	-2.025** (0.685)	5.261*** (0.057)	6.053*** (0.075)
ln X_1	β_1	0.012 (0.015)	-0.414*** (0.142)	-0.457*** (0.152)	0.291** (0.152)	0.201 (0.255)	0.214 (0.213)	0.305*** (0.018)
ln X_2	β_2	-0.032*** (0.004)	-0.926* (0.513)	0.522*** (0.086)	-0.904*** (0.136)	1.251*** (0.192)	0.052*** (0.006)	0.137 (0.115)
ln X_3	β_3	-0.022** (0.015)	0.562 (0.428)	0.125** (0.056)	-0.012* (0.006)	0.204** (0.141)	0.032*** (0.000)	-0.092 (0.087)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
lnX ₄	β ₄	0.025 (0.032)	-0.269 (0.552)	-0.251 (0.239)	0.241 (0.223)	-0.028 (0.245)	-0.029 (0.028)	-0.073 (0.140)
R ²		76.54%	88.79%	83.21%	77.45%	70.51%	82.74%	84.17%

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *
 Source: own calculations based on Eurostat n.d.

The data in Table 3 show that among the countries classified as Moderate Innovators, in the long term, an increase in the X₁ variable (*percentage of the population aged 25–34 with tertiary education*) causes a significant (significance level – 0.01) increase in JJ_2 employee turnover and EU flows (significance level – 0.05) but a significant decrease in the EU and EI variables (significance level – 0.01), ceteris paribus.

Table 4. Evaluation of long-term relationship parameters in models estimated with the FMOLS estimator for the group of countries classified as Emerging Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		lnEE	lnEU	lnEI	lnUE	lnIE	lnJJ_1	lnJJ_2
const	β ₀	5.593*** (0.131)	-7.935 (5.556)	-2.602 (2.159)	-5.907*** (1.967)	-10.595*** (2.199)	-7.132*** (1.257)	-3.643 (2.958)
lnX ₁	β ₁	-0.057*** (0.016)	0.197*** (0.012)	1.579*** (0.299)	1.676*** (0.509)	2.757*** (0.596)	0.517*** (0.012)	1.498*** (0.178)
lnX ₂	β ₂	-0.003 (0.002)	0.529*** (0.157)	0.053*** (0.017)	-0.303*** (0.053)	0.052*** (0.019)	0.641*** (0.117)	0.071*** (0.021)
lnX ₃	β ₃	-0.016 (0.010)	0.263* (0.150)	0.550*** (0.165)	0.072 (0.152)	-0.290 (0.196)	0.973 (0.760)	0.499*** (0.110)
lnX ₄	β ₄	-0.105*** (0.025)	-3.672*** (0.951)	-1.006** (0.515)	0.967*** (0.359)	0.696*** (0.120)	1.772*** (0.501)	-1.706** (0.234)
R ²		78.24%	77.32%	79.27%	87.92%	80.57%	86.55%	89.36%

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *
 Source: own calculations based on Eurostat n.d.

It can thus be concluded that an increase in the X₂ variable (*percentage of the population aged 25–64 involved in lifelong learning*) significantly increases (significance level – 0.01) EI and IE employee flows and JJ_1 turnover, while significantly reducing the EE and EU employee flows (ceteris paribus). A positive and significant impact (significance level – 0.05) of the X₃ variable (*enterprises that provide training to develop or upgrade their personnel’s ICT skills*) is visible in the EI, IE flows (significance level – 0.05) and the JJ_1 turnover (significance level – 0.01), while a negative influence is visible in EE flows (significance level – 0.05). An increase in the X₄ variable (*employ-*

ment in knowledge-intensive activities (% of total employment)) in the long term does not significantly affect any type of employee flow.

The data in Table 4 show that among countries classified as Emerging Innovators, in the long term, an increase in the X_1 variable (*percentage of the population aged 25–34 with tertiary education*) causes a significant (significance level – 0.01) decrease in EE flows but a significant increase in all other flows, ceteris paribus. It can thus be concluded that the increase in the X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) causes a significant (significance level – 0.01) decrease in EU flows of labour but a significant increase in all the other flows and employee turnover (except for EE flows, in which it has no significant effect), ceteris paribus.

An increase of 1% in the X_3 variable (*enterprises that provide training to develop or upgrade their personnel's ICT skills*) causes, at the significance level of 0.05, an increase in EI employee flows by an average of approx. 0.55% and an increase in JJ_2 turnover by an average of approx. 0.499%, ceteris paribus. The impact of the X_3 variable on other types of employee flows is not statistically significant at the 0.05 significance level. An increase in the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) in the long term significantly (significance level – 0.01) reduces EE and EU flows, JJ_2 turnover and EI flows (significance level – 0.05) while significantly (significance level – 0.01) increasing UE and IE flows and JJ_1 turnover, ceteris paribus.

The short-term flexibility assessments for labour market flows in all four groups of countries with different levels of innovation, as obtained in the panel ECM models, are presented in Tables 5–8.

Table 5. Short-term flexibility assessments for labour market flows in panel ECM models for Innovation Leaders (data from 2011–2019)

Variable	Parameter	Dependent variable						
		$\Delta \ln EE_{it}$	$\Delta \ln EU_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln UE_{it}$	$\Delta \ln IE_{it}$	$\Delta \ln JJ_1_{it}$	$\Delta \ln JJ_2_{it}$
$\Delta \ln X_{1,i,t-1}$	α_{21}	0.063* (0.034)	-1.309 (3.387)	-0.636* (0.340)	1.139 (0.834)	1.003 (3.717)	2.043 (2.268)	-4.188 (3.457)
$\Delta \ln X_{2,i,t-1}$	α_{22}	0.017** (0.008)	-0.347 (0.270)	-0.113* (0.061)	-0.173 (0.201)	-0.180*** (0.007)	0.170*** (0.038)	3.208*** (0.952)
$\Delta \ln X_{3,i,t-1}$	α_{23}	-0.007** (0.003)	-0.038 (0.133)	0.139*** (0.044)	-0.136*** (0.043)	0.133 (0.198)	0.138*** (0.017)	0.426*** (0.157)
$\Delta \ln X_{4,i,t-1}$	α_{24}	0.117** (0.037)	-3.030*** (0.817)	-0.710** (0.394)	-1.093** (0.486)	-1.036*** (0.336)	-0.028 (0.033)	-0.228*** (0.051)
$ECT_{i,t-1}$	γ	-0.006*** (0.001)	-0.027 (0.035)	-0.056*** (0.010)	-0.021** (0.008)	-0.032 (0.027)	-0.014*** (0.005)	-0.018*** (0.002)

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *

Source: own calculations based on Eurostat n.d.

For Innovation Leaders in the short-term perspective, a change in the X_1 variable (*percentage of the population aged 25–34 with tertiary education*) in the previous period significantly (significance level of 0.1) increases the EE flows of employees and reduces the EI flows for the current period, ceteris paribus. An increase in the X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) during the previous period causes a significant (significance level of 0.01) decrease in the IE and EI flows during the current period (significance level of 0.1). It also causes a significant increase (significance level of 0.01) during the current period of both JJ employee turnovers and EE employee flows (significance level of 0.01).

An increase of 1% in the X_3 variable (*enterprises that provide training to develop or upgrade their personnel’s ICT skills*) during the previous period causes an increase in the EI employee flows during the current period by an average of approx. 0.138% and in the JJ_2 turnover by an average of approx. 0.426%, at the significance level of 0.01. It also causes an increase in the EI flows by an average of 0.139%, but a decrease in UE flows by 0.136%, ceteris paribus. An increase in this variable during the previous period also causes a decrease in the volume of EE flows during the current period at the significance level of 0.05, ceteris paribus. An increase in the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) during the previous period causes in the current period a decrease in the EU and IE flows and the JJ_2 turnover at the significance level 0.01. It also causes a decrease in the EI and UE flows at the 0.05 significance level, ceteris paribus. An increase in this variable during the previous period also causes an increase in the volume of EE flows during the current period at the significance level of 0.05, ceteris paribus. Based on the analysis of the coefficients that modify the ECT, it can be concluded that the mechanism of achieving equilibrium is statistically significant (significance level of 0.01) for the EE and EI flows and both JJ employee turnovers. It is also statistically significant for UE flows, but at the significance level of 0.05. The error correction mechanism for the EI variable is the strongest: approximately 4.6% of the imbalance in relation to the long-term growth path is corrected through the short-term adjustment process.

Table 6. Short-term flexibility assessments for labour market flows in panel ECM models for Strong Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		$\Delta \ln EE_{it}$	$\Delta \ln EU_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln UE_{it}$	$\Delta \ln I_{it}$	$\Delta \ln JJ_1it$	$\Delta \ln JJ_2it$
$\Delta \ln X_{1,i,t-1}$	α_{21}	0.014 (0.010)	0.573 (0.510)	-0.058*** (0.012)	-0.119*** (0.011)	-0.101 (0.111)	-0.069*** (0.016)	-0.161*** (0.035)
$\Delta \ln X_{2,i,t-1}$	α_{22}	-0.056*** (0.008)	1.145*** (0.377)	0.103 (0.107)	0.151 (0.109)	-0.111 (0.094)	0.181*** (0.019)	0.064 (0.054)

Variable	Parameter	Dependent variable						
		$\Delta \ln EE_{it}$	$\Delta \ln EU_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln UE_{it}$	$\Delta \ln IE_{it}$	$\Delta \ln JJ_1_{it}$	$\Delta \ln JJ_2_{it}$
$\Delta \ln X_{3,i,t-1}$	α_{23}	0.005 (0.003)	-0.038 (0.253)	0.015 (0.024)	0.004 (0.054)	0.010 (0.038)	-0.007 (0.006)	-0.022*** (0.002)
$\Delta \ln X_{4,i,t-1}$	α_{24}	-0.011 (0.053)	-1.554*** (0.235)	-0.049 (0.180)	-0.175*** (0.017)	-0.103*** (0.001)	-0.087*** (0.018)	-0.051*** (0.014)
$ECT_{i,t-1}$	γ	-0.015 (0.011)	-0.046*** (0.001)	-0.011 (0.085)	-0.009*** (0.01)	0.016 (0.022)	-0.02*** (0.002)	-0.036*** (0.01)

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *

Source: own calculations based on Eurostat n.d.

For the Strong Innovators group in the short-term perspective, a 1% increase in the X_1 variable (*percentage of the population aged 25–34 with tertiary education*) during the previous period causes a decrease in the current period (significance level of 0.01) in the following employee flows: EI by about 0.058% on average, UE by 0.119% on average, JJ_1 by 0.069% on average, and JJ_2 by 0.161% on average, ceteris paribus. In the same countries and also in the short term, a 1% increase in the X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) during the previous period causes a decline in the EE flows (significance level of 0.10) during the current period by an average of approx. 0.056%, ceteris paribus. It also caused a significant (by 1.145% on average) increase in the EU flows and an increase in employee turnover in the 15–24 age group by about 0.181%, on average, ceteris paribus. A significant (significance level of 0.01) increase in the value of the X_3 variable (*enterprises that provide training to develop or upgrade their personnel's ICT skills*) during the previous period causes a significant (significance level of 0.01) reduction in the JJ_2 turnover during the current period and does not significantly affect the remaining flows.

The X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) in the short term did not have a significant impact on any employee flow, with a significance level of 0.05 within the Strong Innovators group. An increase in the X_3 variable (*enterprises that provide training to develop or upgrade their personnel's ICT skills*) during the previous period causes a reduction in the JJ_2 turnover during the current period at the significance level of 0.01, ceteris paribus. An increase in the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) during the previous period causes a decrease (significance level 0.01) in the current period in the following flows: EU, UE, IE, JJ_1, and JJ_2, ceteris paribus. Negative values of the parameters that modify the ECT show that the EE, EU, UE, EI, JJ_1, and JJ_2 employee flows reached equilibrium as a result of the short-term adjustment mechanism, and that this mechanism is statistically significant at the 0.01 level only for the EU and UE flows and JJ_1 and JJ_2 turnovers. With the EU variable, the error correction mech-

anism is the strongest: about 4.6% of the imbalance of the long-term growth path is corrected with the short-term adjustment process.

Table 7. Short-term flexibility assessments for labour market flows in panel ECM models for Moderate Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		$\Delta \ln EE_{it}$	$\Delta \ln EU_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln UE_{it}$	$\Delta \ln E_{it}$	$\Delta \ln JJ_1_{it}$	$\Delta \ln JJ_2_{it}$
$\Delta \ln X_{1,i,t-1}$	α_{21}	0.004 (0.006)	-0.121* (0.066)	-0.146** (0.065)	0.100 (0.061)	0.091 (0.066)	0.253*** (0.008)	1.079*** (0.084)
$\Delta \ln X_{2,i,t-1}$	α_{22}	-0.009*** (0.002)	-0.258 (0.322)	0.166*** (0.040)	-0.253*** (0.080)	0.266*** (0.048)	0.153 (0.172)	0.127*** (0.094)
$\Delta \ln X_{3,i,t-1}$	α_{23}	-0.009 (0.006)	0.156 (0.152)	0.026 (0.020)	-0.003 (0.005)	0.084* (0.050)	0.042*** (0.025)	0.099 (0.083)
$\Delta \ln X_{4,i,t-1}$	α_{24}	0.012 (0.009)	-0.126*** (0.006)	-0.119 (0.101)	0.109 (0.096)	-0.012 (0.104)	0.015*** (0.001)	0.043 (0.057)
$ECT_{i,t-1}$	γ	-0.022 (0.035)	-0.061*** (0.014)	-0.043*** (0.009)	-0.044*** (0.005)	-0.019 (0.011)	-0.063*** (0.021)	-0.057** (0.026)

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *
Source: own calculations based on Eurostat n.d.

In the Moderate Innovators group, a change in the X_1 variable (*percentage of the population aged 25–34 with tertiary education*) during the previous period causes during the current period an increase (significance level of 0.01) of employee turnovers JJ_1 and JJ_2 and a decrease at the significance level of 0.05 in the EI flows.

An increase in the X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) in the previous period causes an increase (significance level of 0.01) in the EI and IE flows and the JJ_2 turnover in the current period, and a decrease in the EE and UE flows at the same significance level (0.01) in this group, ceteris paribus. An increase in the X_3 variable (*enterprises that provide training to develop or upgrade their personnel's ICT skills*) during the previous period causes a significant increase in the JJ_1 turnover (at the significance level of 0.01) and an increase in the IE flows (at the significance level of 0.1), without significantly affecting other flows and turnovers. An increase in the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) during the previous period causes a decrease (significance level 0.01) in the UE flows in the current period, ceteris paribus. Negative assessments of the parameters at the ECT show that all flows and turnovers are equilibrated as a result of short-term adjustments, and this mechanism is statistically significant (at the 0.01 level) only for the EU, UE, and EI flows and both JJ_1 and JJ_2 turnovers. With the JJ_1 variable, the error correction mechanism is the strongest:

approximately 6.3% of the imbalance of the long-term growth path is corrected by short-term adjustments.

Table 8. Short-term flexibility assessments for labour market flows in panel ECM models for Emerging Innovators (data from 2011–2019)

Variable	Parameter	Dependent variable						
		$\Delta \ln EE_{it}$	$\Delta \ln EU_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln UE_{it}$	$\Delta \ln EI_{it}$	$\Delta \ln JJ_{1it}$	$\Delta \ln JJ_{2it}$
$\Delta \ln X_{1,i,t-1}$	α_{21}	-0.016*** (0.005)	0.066*** (0.004)	0.511*** (0.099)	0.591*** (0.063)	0.971*** (0.191)	0.205*** (0.009)	0.791*** (0.084)
$\Delta \ln X_{2,i,t-1}$	α_{22}	-0.003 (0.003)	0.161** (0.071)	0.010 (0.009)	-0.115*** (0.014)	0.020 (0.099)	0.321*** (0.054)	0.036*** (0.014)
$\Delta \ln X_{3,i,t-1}$	α_{23}	-0.005 (0.004)	0.094 (0.079)	0.140** (0.064)	0.013 (0.055)	-0.093 (0.064)	0.443 (0.331)	0.187*** (0.052)
$\Delta \ln X_{4,i,t-1}$	α_{24}	-0.030*** (0.007)	-1.055*** (0.111)	-0.199* (0.109)	0.179*** (0.053)	0.100*** (0.021)	0.852*** (0.318)	-0.876** (0.014)
$ECT_{i,t-1}$	γ	-0.006*** (0.001)	-0.086*** (0.024)	-0.054 (0.069)	-0.042*** (0.003)	0.040 (0.042)	-0.063*** (0.015)	-0.075*** (0.033)

The significance levels of 0.01; 0.05 and 0.1 are marked respectively with ***, ** and *

Source: own calculations based on Eurostat n.d.

In the Emerging Innovators group, a change in the X_1 variable (*percentage of the population aged 25–34 with tertiary education*) during the previous period causes a significant (significance level of 0.01) decrease in the EE flows during the current period and a significant (same level of significance) increase in all the other flows and turnovers, *ceteris paribus*. An increase in the X_2 variable (*percentage of the population aged 25–64 involved in lifelong learning*) during the previous period causes a significant (significance level of 0.01) decrease in UE flows during the current period and a significant (significance level of 0.05) increase in EU flows. It also causes a significant (significance level of 0.01) increase in both JJ turnovers. A one-per-cent increase in the X_3 variable (*enterprises that provide training to develop or upgrade their personnel's ICT skills*) during the previous period causes an increase in the JJ_2 turnover by about 0.187% and in the EI flows by approx. 0.14% on average during the current period, at the significance level of 0.01, *ceteris paribus*. The variable X_3 shows no statistically significant impact on the other types of flows. An increase in the value of the X_4 variable (*employment in knowledge-intensive activities (% of total employment)*) during the previous period causes a decrease in the current period in the EE and EU flows and the JJ_2 turnover, at the significance level 0.01, *ceteris paribus*. It also causes an increase in the EI and UE flows and the JJ_1 turnover at the same level of significance, *ceteris paribus*. Upon analysis of the parameters modifying the ECT , it can be concluded that equilibrium is achieved by all flows except for EI, and the mechanism of achieving equilibrium

is statistically significant (significance level of 0.01) only for the EE, EU, and UE flows. The error correction mechanism is the strongest for the EU variable: approximately 8.6% of the imbalance in the long-term growth path is corrected through short-term adjustments.

Conclusions

The long-term development prospects of economies depend on their ability to innovate. Innovation is one of the significant factors that determine an economy's competitiveness. Although innovation is a key driver of the competitiveness of individual economies today, to the best of the authors' knowledge, there has been no empirical research on the impact of the economy's innovativeness on labour market flows. Our empirical results demonstrate significant and persistent differences in the scale and structure of labour market flows, which depend on the level of innovation in an economy. The economy's level of innovativeness determines specific flow patterns in the relevant labour market. The results are largely consistent with Elsby, Hobijn, and Sahin (2011), who stated that labour markets follow geographical patterns, i.e. relatively large groups of countries show similar dynamic labour market flows pattern.

The study involved an in-depth analysis of the impact of the level of economies' innovativeness on labour market flows. The results indicate that the level of an economy's innovativeness affects both the dynamics and the structure of flows in the labour market. The higher the innovativeness, the greater the dynamics of flows in the labour market, especially of the job-to-job type. In countries that are Innovation Leaders, participation in lifelong learning allows employees to maintain their employment status and, at the same time, upgrade to a better job. In countries that are Emerging Innovators, participation in lifelong learning and acquiring new digital skills increases the turnover of employees, mainly the young ones (15–24 y/o). However, it is accompanied by a change of status in the labour market. In economies where the level of innovation is high (Innovation Leaders), employees often change jobs but not their labour market status.

Innovative economies demonstrate stable employment statuses, i.e. a high rate of transitions from employment to employment (EE) and, at the same time, a high turnover of employees (job-to-job). Workforce flows between workplaces are a natural phenomenon. People keep looking for better-paid jobs and/or jobs that would allow them to develop new skills or acquire new qualifications. Employees move smoothly from one job to another, and the transition is accompanied by a flow of knowledge, further stimulating innovative activities. Employees most often change jobs having been offered a higher salary and professional development opportunities. Employee turnover leads to better allocation of labour resources and in-

creased productivity. It allows for a better person–job fit and stimulates innovation through the exchange of experience and knowledge between companies (Breschi and Lissoni 2009, pp. 439–468).

The analysis showed that in countries with a low level of innovativeness, i.e. Moderate Innovators or Emerging Innovators, employees change jobs much less frequently than in countries with a high level. Similar conclusions were reached by Pieroni and Pompei (2008), who showed that in the Italian economy (Moderate Innovators), companies more often use internal labour resources; hence, employee turnover is lower.

In more innovative countries, there are more opportunities to change jobs, but seeking such opportunities implies the need to continuously upgrade qualifications and update the knowledge acquired during formal education. An innovative (including digital) economy expects much more from its workforce. It requires life-long professional development, not only in youth, as employees must have up-to-date and useful knowledge at all times, even if their status changes very quickly. Our analysis shows that in countries classified as Innovation Leaders, the most important determiner of employee “job-to-job” turnover in the 15–24 age group (JJ_1) is the *percentage of the population aged 25–64 involved in lifelong learning* (X_2), while in Emerging Innovators, it is *enterprises that provide training to develop ICT skills* (X_3).

In countries with less innovativeness, it is the shortages of digital skills among (mainly young) employees that constitute a barrier to employee flows between companies. Haldane (2019) reached similar conclusions when analysing employment in the United Kingdom. Companies in EU countries increasingly highlight workers’ skill shortages in many professions and industries. Technological progress, associated with widespread digitisation and innovation, increases the demand for new skills and new types of work. It requires employees to constantly develop, acquire new skills and look for new roles. Our research confirmed that an economy’s innovation level determines relevant behaviours among employees. Keeping a position is increasingly associated with improving qualifications and acquiring new skills. The analysis presented in the article allows for a better understanding of labour market phenomena today.

The analysis has some shortcomings that determine possible directions for further research. The degree of heterogeneity of the labour market participants should be better considered, and not only between but also within the resource groups, i.e. the employed, the unemployed and the economically inactive. It should be expected that decomposing aggregate data on labour market resources, for instance, with the employed (by age, gender, education level or type of contract (temporary vs permanent)) might lead to conclusions that are both interesting and valuable from the point of view of an economy’s level of innovation. Moreover, taking into account the digital skills of employees, especially those of Generations Y and Z, would make it possible to assess their situation in the era of the 4th Industrial Revolu-

tion. It is one of the most important challenges in the European Union (Morandini, Thum-Thyssen, and Vandeplas 2020). According to the results of the DESI (Digital Economy and Society Index) research, more than 40% of Europeans still do not have basic IT skills. These deficiencies create a barrier to development both at the individual level (e.g. they deepen the existing socio-economic inequalities) and at the aggregate level (e.g. they hinder the introduction of new technologies at enterprises). The aforementioned issues determine the further direction of our research to analyse the significance of flows between employee resources in the labour market in economies with different levels of innovation.

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Analiza wpływu innowacyjnych uwarunkowań gospodarki na przepływy pracowników na rynku pracy w państwach Unii Europejskiej

Głównym celem pracy jest przedstawienie wyników badań empirycznych dotyczących wpływu poziomu innowacyjności gospodarki na strukturę przepływów na rynku pracy.

Analiza kierunków i skali przepływów umożliwia poznanie ważnych własności rynku pracy, a tym samym pozwala lepiej konstruować i adresować polityki ukierunkowane na ograniczanie skali bezrobocia lub aktywizację osób biernych zawodowo. W opracowaniu wykorzystano dane z badania Labour Force Survey (LFS) oraz statystyk eksperymentalnych *job-to-job* dla państw Unii Europejskiej w latach 2011–2019. Badania przeprowadzono odrębnie dla wyróżnionych grup państw ze względu na poziom innowacyjności, tj. Liderzy innowacji (*Innovation leaders*), Silni innowatorzy (*Strong innovators*), Umiarkowani innowatorzy (*Moderate innovators*), Wschodzący innowatorzy (*Emerging innovators*). Wskazujemy, że skala i kierunek przepływów osób na rynku pracy zależą od poziomu innowacyjności gospodarki. Głównym wkładem opracowania jest zidentyfikowanie wzorców przepływów na rynku pracy w państwach Unii Europejskiej, warunkowanych poziomem innowacyjności gospodarki. W badaniu wykorzystano panelowe modele korekty błędem ECM oraz panelowy test przyczynowości. W krajach zaliczanych do Liderów innowacyjności kształcenie ustawiczne zwiększa przepływy pracowników (EE) oraz rotację (*job-to-job*) ogółem, natomiast w krajach słabych innowacyjnie wzrasta rotacja jedynie wśród osób młodych (15–24 lata).

Słowa kluczowe: przepływy na rynku pracy, zmiany statusu osób na rynku pracy, rotacja pracowników, innowacyjność gospodarki