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The Dynamic Relationship between Technological Change and Employment: A Comparison of Youth and Total Employment using Panel VAR Approach and Causality Analysis

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Teknolojik Değişme ve İstihdam Arasındaki Dinamik İlişki: Genç İstihdamı ile Toplam İstihdamın Panel VAR ve Nedensellik Analizleri ile Karşılaştırılması

Abstract

This study empirically examines the relationship and causality between technological change and employment by comparing youth and total employment. It covers data from 16 OECD economies from 1985 to 2018 and uses multifactor productivity (MFP) as a proxy for technological change. The findings from the general method of moments panel vector autoregression (GMM Panel-VAR) approach indicate significant and positive effects of MFP on youth and total employment, and a significant yet negative impact of youth employment on MFP. According to Panel-VAR-Granger-Causality analysis results, there is a two-way causality between MFP and youth employment and a one-way causality from MFP to total employment. Thus, this study empirically confirms the job-creation effect of technology and finds out that the technological change and employment nexus differs for youth employment compared to that for total employment.

Keywords : Technological Change, MFP, Multifactor Productivity, Youth Employment, Employment, Job-Creation, Panel VAR, Panel VAR Granger-Causality.

JEL Classification Codes : O33, O11, J21, O50.

Öz

Bu çalışma teknolojik değişme ile istihdam arasındaki ilişkiyi ve nedenselliği, genç istihdamı ile toplam istihdamı karşılaştırarak, ampirik olarak incelemektedir. Çalışma, 16 OECD ülkesi için 1985-2018 arası dönemdeki verileri kapsamakta olup teknolojik değişmenin göstergesi olarak çoklu faktör verimliliğini (ÇFV) kullanmaktadır. Genelleştirilmiş Momentler Panel Vektör Otoregresif (GMM Panel-VAR) analizi bulguları, ÇFV'nin genç ve toplam istihdamın üzerinde anlamlı ve pozitif etkisinin bulunduğunu; genç istihdamın ÇFV üzerindeki etkisinin ise anlamlı fakat negatif olduğunu göstermektedir. Panel VAR-Granger Nedensellik analizi bulgularına göre ise ÇFV ile genç istihdamı arasında çift-yönlü, ÇFV'den toplam istihdama doğru ise tek-yönlü nedensellik bulunmaktadır. Böylelikle bu çalışma ile teknolojik değişmenin iş yaratma etkisi ampirik olarak doğrulanmakta ve teknolojik değişme-istihdam ilişkisinin genç istihdamı için, toplam istihdama kıyasla, farklı olduğu sonucunu ulaşılmıştır.

Anahtar Sözcükler : ÇFV, Çoklu Faktör Verimliliği, Genç İstihdamı, İstihdam, İş Yaratma, Panel VAR, Panel VAR-Granger Nedensellik.

1. Introduction

Youth constitute one of the vulnerable groups in labour markets, as their access to labour market opportunities is relatively limited compared to adults. Even if they reach employment opportunities, they may face some difficulties due to their lack of experience. They are generally paid low wages and may be at the top of the list to lose their jobs in an economic downturn (Caliendo & Schmidl, 2016: 1; Maguire et al., 2013: 196). In addition, labour market opportunities may be insufficient to provide decent jobs to youth. Their lack of inexperience may result in many difficulties, which in turn cause them to work in precarious jobs (ILO, 2020: 15-6). Considering all these, youth employment[1] can be regarded as more sensitive to economic fluctuations and can be affected significantly by many economic factors.

One of the most important economic factors has been technological change which had shown a rapid increase from the 1980s until the 2008 crisis and slowed down afterwards (OECD, 2018: 52). The impact of technological change on employment is specifically crucial for the youth because new jobs are held mainly by machines or artificial intelligence. As newly graduates or as lowly experienced individuals, youth mostly feel threatened that they may remain idle because of the displacement of workers by machines (ILO, 2020: 14). From this point of view, it is crucial to examine employment and technological change nexus, particularly for the youth. Aside from youth employment, there has been no consensus on the nexus of (total) employment and technological change to date. The latter's impact on the former is accepted as negative according to some studies, whereas it is argued to be positive according to others. The supporters of the first view put forward those advances in process innovation result in lower usage of factors of production. In most cases, labour is saved during the production phase. Such a decline in labour is regarded as the labour-saving effect of technology which is argued to be offset by compensation theory, another impact resulting from technological change. According to the compensation theory, technology may first result in higher usage of capital (machines) and lower usage of labour (Piva & Vivarelli, 2017: 4). Yet, after a while, demand for labour is expected to increase because the production of new capital will require higher labour. Compensation theory can take place through many mechanisms, including the production of new machines, changing investment structures, lower price levels, and wages (Campa, 2018: 63; Marx, 2015 [1867]: 293; Ricardo, 2018 [1821]: 350; Piva & Vivarelli, 2017: 4-5). On the other hand, the supporters of the second view argue that the different type of innovation, product innovation, yields a higher level of employment through the production of new goods. This is regarded as the job creation effect of technology (Piva & Vivarelli, 2017: 10). Even though some

[1] *The youth is generally used to refer individuals either aged 15-24 years or aged 15-29 years. (Eurofound, 2012: 3, 21). An examination of the 25-29 age group is also crucial in youth employment studies as the group mostly includes individuals with little experience or new entrants. Thus, in addition to the 15-24 age-group, the 25-29 age-group is also more sensitive to business fluctuations compared to the adults (Görkey, 2019: 225). For this reason, this study considers the 15-29 age group for its youth definition and investigate the youth employment accordingly.*

studies discuss that the positive effects of technology are more effective on employment compared to the negative effects (Alic, 1997: 1), there is still no agreement on the relevant nexus in the literature.

The literature on the relationship between employment and technological change includes many studies that differ in their level of analysis. The vast of the literature comprises firm-level studies (Coad & Rao: 2011; Evangelista & Vezzani, 2012; Falk, 2012; Lachenmaier & Rottmann, 2011; Piva & Vivarelli, 2004, 2018; Van Roy et al., 2018) and industry-level studies (Bogliacino & Vivarelli, 2012; Buerger et al., 2012; Dosi et al., 2019; Piva & Vivarelli, 2017); both of which mostly empirically evidence employment creation effects of technology. However, the studies that examine the relevant nexus at the macro-level are quite limited, and the findings from these indicate either mixed results (Simonetti et al., 2000: 42; Tancioni & Simonetti, 2002: 185; Vivarelli, 1995) or negative effects (Pini, 1995: 208). According to Piva & Vivarelli (2017: 13), macro-level studies offer mixed findings because the empirical findings are subject to changes depending on the proxy for technological change used in studies. On the other hand, macro-level studies are more successful in presenting the overall effect of technological change on employment as they cover all parts of economies. Thus, empirical findings from macro-level studies are more likely to indicate whether the compensation effect of technological change fully works or not (Matuzeviciute et al., 2017: 5; Piva & Vivarelli, 2017: 15).

The limited macro-level literature on the relationship between employment and technological change shows that no study in the literature examines the issue specifically for the youth. Reading the relevant nexus in youth is crucial considering the sensitivity of youth in labour markets. In addition to this, it is not only technological change that affects employment, but it is also employment that results in changes in technological level through skill structures (Greenan, 2003: 288). Thus, employment and technological change are subject to a mutual relationship. However, the relevant nexus is only examined as a one-way relationship, from technological change to employment. Moreover, technological change and employment are not only affected by each other but also by their own past values. Thus, examining the relevant relationship using dynamic econometric models is crucial.

This study aims to contribute to the literature by empirically examining the dynamic relationship and causality between employment and technological change by comparing youth and total employment. Such a comparison is crucial because the employment and technological change nexus may be different for the youth than for total employment when one considers the higher sensitivity of youth employment to business fluctuations. The study uses multifactor productivity (MFP) for the technological change variable. Applying the general method of moments (GMM) panel vector autoregression (VAR) approach and panel Granger-causality Analysis as the methodology, the study covers 16 OECD countries from 1985 to 2018. Accordingly, the contribution of this study to the literature is threefold. First, it investigates the relationship focusing on youth employment and compares the findings to total employment. Second, it examines the relevant nexus mutually. Lastly, the mutual relationship is investigated dynamically rather than statically. The study also includes a discussion that provides a basis for future research directions and policy recommendations.

The rest of the study is organised as follows: Section 2 reviews the empirical literature, section 3 describes the data and the methodology, section 4 presents empirical findings, section 5 makes a discussion and offers policy recommendations, and section 6 concludes the study.

2. Empirical Literature Review

Many studies focus on the relationship between employment and technological change. Most of these studies have examined the impact of technological change on employment and aim to empirically find out whether technological change results in employment creation or destruction. The majority of these studies have examined the topic either at the firm level (Coad & Rao: 2011; Evangelista & Vezzani, 2012; Falk, 2012; Lachenmaier & Rottmann, 2011; Piva & Vivarelli, 2004, 2018; Van Roy et al., 2018) or at the industry-level (Bogliacino & Vivarelli, 2012; Buerger et al., 2012; Dosi et al., 2019; Piva & Vivarelli, 2017).

The findings from firm-level analysis mainly indicate significant and positive effects of technological change on new job opportunities. Van Roy et al. (2018: 762) analysed the impact of innovation on job-creation effect in twenty-thousand patenting firms in Europe from 2003-2012 using the GMM-SYS estimator. Empirical evidence from this study showed that innovation positively affects job opportunities only in high-technology manufacturing sectors. Using firm-level data in Europe, Piva & Vivarelli (2018: 5, 10-1) investigated the labour impact of R&D expenditures and found positive effects only in medium and high-technology sectors. Piva & Vivarelli (2004: 374-5) examined the relationship between innovation and employment using GMM-SYS panel data analysis and found a positive yet low impact of innovation on employment in Italian firms in the 1990s. The labour-friendly effect of technological change was also evidenced in Falk (2012: 19), which analysed the effect of R&D on employment growth in Austrian firms from 1995 to 2016. Coad & Rao (2011: 255), Evangelista & Vezzani (2012: 889-92), and Lachenmaier & Rottman (2011: 218) also confirmed the employment creation effect of technology at the firm level. The literature clearly shows that numerous firm-level studies have mainly evidenced the positive impact of technological change on employment.

The literature is also rich in studies focusing on the industry-level issue. Piva & Vivarelli (2017: 17, 26) examined the impact of technological change on employment by using R&D expenditures as a measure of technological change. This study focused on the manufacturing and services industries in European economies from 1998 to 2011 using dynamic panel data analysis. It found out that technological change yields a positive impact in medium and high-technology sectors. Dosi et al. (2019: 13-18) investigated whether embodied and disembodied technological change result in more jobs or destroys existing ones in upstream and downstream sectors. It covered 19 European countries between 1998 and 2016 and found that disembodied technological change positively affected employment in the upstream sectors. On the other hand, employment increased by embodied technological change in downstream sectors. Covering sectoral data in 15 European economies from 1996 to 2005, Bogliacino & Vivarelli (2012: 96, 105-8) analysed the impact of R&D expenditures on job creation. Empirical findings from GMM-SYS panel data analysis confirmed that R&D creates new jobs. Buerger et al. (2012: 576-7) investigated the job-creation effect of innovation and found either positive or no significant impact on industries in Germany.

Contrary to the rich empirical literature at the firm and industry-level studies, the studies that focus on the issue at the macro level are quite limited (Pini, 1995; Simonetti et al., 2000; Tancioni & Simonetti, 2002; Vivarelli, 1995). While firm and industry-level studies mainly indicate the labour-friendly impact of technological change, macro-level studies present mixed results. Using aggregate annual data for the US and Italy, Vivarelli (1995) found out that the labour-saving impact of technological change could only be partially eliminated. Simonetti et al. (2000: 34, 42) examined the effect of innovation on 4 OECD economies from 1965 to 1993 using 3SLS analysis. This study distinguished the compensation effect of technology in its empirical evidence, which indicated mixed results. Tancioni & Simonetti (2002: 185) studied the employment impact of technology in the US and Italy by extending the empirical model of Vivarelli (1995). This study considered the effect of trade and economic growth, as well. The findings of this study presented mixed findings depending on the type of compensation effect of technology. Finally, Pini (1995: 194, 208) investigated the employment and technological change nexus for a panel of 9 OECD economies from 1960-1990 and found a negative impact of the innovation process on employment through the capital. In addition to this, the study also evidences the compensation mechanism through exports.

Table 1 shows the summary of mentioned studies from the empirical literature. The empirical literature review indicates a gap in recent macroeconomic studies because the nexus has not been examined for a long time. The empirical findings from the existing studies show mixed findings. Thus, there is no consensus on the relevant nexus at the macro-level. In addition, no study in the literature focuses on the issue of youth employment. This study aims to fill the relevant gaps in the literature.

Moreover, this study is the first attempt in the literature to examine the relevant nexus using dynamic econometric methods and causality analyses. It is crucial to investigate the mutual effect of technological change and employment using dynamic methods because the past values of macroeconomic variables are effective on their present values (Yerdelen-Tatoğlu, 2020: 115). Thus, this study empirically examines the dynamic relationship and causality between employment and technological change by comparing youth employment to total employment. It aims to reveal whether such a connection is empirically different for youth employment than total employment.

Table: 1
Empirical Literature Review Summary

Level	*Author(s) and year*	*Data & Method*	*Findings*
Firm-level	Van Roy et al. (2018)	Europe firms, 2003-2012, GMM-SYS	Innovation positively affects job opportunities only in high-technology manufacturing sectors.
	Piva & Vivarelli (2018)	Firms from manufacturing and services sectors in 11 European countries, 1998-2011, GMM-SYS and LSDVC	The positive impact of R&D expenditures on labour only in medium and high-technology sectors and capital formation negatively affects employment.
	Piva & Vivarelli (2004)	Italian manufacturing firms, 1992-1997, GMM-SYS and OLS.	Positive yet low impact of innovation on employment.
	Falk (2012)	Austrian firms, 1995-2016, Quantile regression	R&D activities increase employment.
	Coad & Rao (2011)	USPTO Patent data from 1920 firms, patents granted between 1962-2002 and citations between 1975-2002.	Innovative activity creates employment at the firm level.
	Evangelista & Vezzani (2012)	Firm-level CIS4 (2002-2004) data from selected EU countries, index generation.	The indirect positive impact of innovation on employment at the firm level.
	Lachenmaier & Rottman (2011)	German manufacturing firms, 1982-2003, GMM-SYS.	Innovation affects employment positively with a time-lag at the firm level. The impact of process innovation is higher than that of product innovation.
Industry-level	Piva & Vivarelli (2017)	Manufacturing and services industries in European economies, 1998-2011, dynamic panel data	Technological change positively affects employment in medium and high-technology sectors.
	Dosi et al. (2019)	Upstream and downstream sectors in 19 European countries, 1998-2016, Panel data	Disembodied technological change affects employment positively in the upstream sectors, while embodied technological change affects employment positively in downstream sectors.
	Bogliacino & Vivarelli (2012)	25 manufacturing and services sectors in 15 European economies, 1996-2005, GMM-SYS panel data.	R&D expenditures lead to the creation of new jobs.
	Buerger et al. (2012)	4 industries in German regions, 1999-2005, VAR model.	Mixed findings for the job-creation effect of innovation in industries.
Macro-level	Vivarelli (1995)	US and Italy, 1960-1988, 3SLS.	Labour-saving impact of technological change can only be partially eliminated.
	Simonetti et al. (2000)	4 OECD economies, 1965-1993, 3 SLS	Mixed findings for the impact of innovation on employment.
	Tancioni & Simonetti (2002)	UK and Italy - extends the study of Vivarelli (1995), ARDL.	Mixed findings for the impact of technology on employment.
	Pini (1995)	9 OECD economies, 1960-1990, 3SLS.	The negative impact of the innovation process on employment through the capital. Evidence for compensation effect through exports.

Source: Compiled by the author.

3. Data and Methodology

3.1. Data

This study examines the dynamic relationship and causality between technological change and employment by distinguishing the latter variable as youth employment and total employment. Thus, the variables used in this study are youth employment, total employment, and MFP as a proxy for technological change. The study covers annual data for 16 OECD economies from 1985 to 2019.

Total employment data are compiled from OECD (2020a) and represent thousands of persons who are 15 years old and over. As mentioned earlier, the youth definition in this study includes individuals between 15-29-year-olds rather than 15-24-year-olds. Accordingly, youth employment data are constructed as the sum of employment from 15 to 24 and 25 to 29 ages. Employment by age statistics is collected from OECD (2020b) statistics and presented in thousands of persons. Finally, MFP data are collected from the OECD Productivity Database (OECD, 2020c) as an index with the base year of 2015. This variable represents spillover effects; thus, it measures technological change. All the variables are expressed in natural logarithms.

The study includes Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, New Zealand, Portugal, Spain, Sweden, the UK, and the US. Sixteen economies limit the analysis because of two reasons. First, not all OECD economies' employment statistics go back to the 1980s. However, it is better to cover a more extended time dimension since the methodologies of this study are panel time-series analysis. Second, MFP statistics are only available for some economies. The study covers a period from 1985 to 2018. Accordingly, covering 16 economies in its cross-section and 34 years in its time dimension, the panel has 544 observations.

Table: 2
Summary Statistics, 16 OECD Economies, 1985-2018

Variable	Obs	Mean	Std. Dev.	Min	Max
lnEMP	544	9,333	1,207	7,192	11,956
lnEMPY	544	7,919	1,193	6,085	10,525
lnMFP	544	4,538	0,0846	4,214	4,676

Source: Author’s calculations.
Notes: lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and multifactor productivity, respectively.

Table 2 presents summary statistics of the variables and shows that the standard deviation of youth employment *(lnEMPY)* is lower than that of total employment *(lnEMP)*. The standard deviation of *lnMFP* can be regarded as low compared to the deviations in the employment variables. Table 2 shows summary statistics for the whole panel. However, it is also important to examine the data by economies when working with panel data. Thus, Figure 1 shows the time series of variables, and Appendix A presents summary statistics by economies.

Figure 1 shows that youth employment *(lnEMPY)* declines in some economies, which is more apparent in Italy, Portugal, and Spain after the 2008 crisis. Thus, the time-series graphs show that the negative impact of the 2008 crisis was more severe on youth employment in the Southern European economies. Figure 1 also shows that the gap between total employment *(lnEMP)* and youth employment *(lnEMPY)* has increased in most economies when one compares the start and the end of the period examined. However, the relevant gap is more significant in Belgium, France, Italy, Portugal, and Spain than in other economies.

Figure: 1
Time-Series by Economies, 1985-2018

Source: Author's calculations.

3.2. Methodology

This study investigates the dynamic relationship and causality between (youth and total) employment and MFP by using the panel VAR approach and causality analysis as the methodology. The panel VAR approach is a technique for panel time series analysis that aims to investigate the dynamic relationship between variables. Frequently used together with the panel VAR approach, causality analysis investigates whether the variables of interest are subject to causation with each other. Because both are time series analyses, stationary variables must be used in analyses (Yerdelen-Tatoğlu, 2018: 123). Accordingly, a preliminary step for these analyses is to apply unit-root tests to check the stationarity of variables.

Examining the cross-sectional dependence of variables is necessary to choose between first- or second-generation unit-root tests. This study used the Pesaran - Cross-Sectional Dependence (Pesaran-CD) (2004) test. CD-test statistic is tested under a null hypothesis of cross-sectional independence. If null is not rejected, first-generation unit-root tests are applied. Otherwise, second-generation unit-root tests are used (Yerdelen-Tatoğlu, 2018: 21, 67). Because the variables are cross-sectionally dependent, this study used Breitung and Pesaran's Cross-Sectionally Augmented Dickey-Fuller (CADF) tests from second-generation unit-root tests. Breitung test was applied by demean function, which subtracts cross-section means from the series to eliminate cross-sectional dependence. Breitung's test statistic and Pesaran CADF's t-bar statistic are tested against a null hypothesis of non-stationarity (Breitung & Das, 2005: 416; Pesaran, 2007: 287). Rejection of the null hypothesis denotes that the series does not contain a unit root. Thus they are stationary and can be used for analysis. On the other hand, if null is not rejected, variables are not stationary and cannot be used in time series analysis. In such a case, the first differences of the variables are tested for Stationarity by repeating the same steps. If the null hypothesis is rejected for the first difference of variables, the variables can be used in their first difference in the analysis. All the variables used in this study were not stationary in their level but became stationary in their first differences. Thus, the first differences (d) were used in the analyses.

This study uses the GMM estimator of the Panel VAR approach. The variables used in the present study are plugged into the empirical model proposed by Holtz-Eakin et al. (1988: 1373). Thus, total employment and youth employment models can be presented in Equations (1) and (2), respectively.

$$dlnEMP_{it} = \propto_{0t} + \sum_{l=1}^{m} \propto_{lt} dlnEMP_{it-1} + \sum_{l=1}^{m} \delta_{lt} dlnMFP_{it-1} + \varphi_t f_i + u_{it} \tag{1}$$

$$dlnEMPY_{it} = \propto_{0t} + \sum_{l=1}^{m} \propto_{lt} dlnEMPY_{it-1} + \sum_{l=1}^{m} \delta_{lt} dlnMFP_{it-1} + \varphi_t f_i + u_{it} \tag{2}$$

where, i denotes OECD economies and t denotes time. α_0 parameters are constants, φ is time effects, f is individual effects and u is the error term. m shows lag length which requires a separate procedure for optimal determination. *lnEMP*, *lnEMPY*, and *lnMFP* are the variables used in this study and they represent natural logarithms of total employment, youth employment, and multifactor productivity (MFP), respectively. All the variables are in their first differences because they are not stationary in their levels and have become stationary in their first differences. This is shown with the letter d in front of the variables. $\propto_{lt}$ and δ_{lt} are the estimated parameters and their statistical significance shows that the relevant variables' impact is significant. All the variables in equations (1) and (2) are endogenous. In addition to this, the equations are in dynamic form because all the endogenous variables are affected by the past values of their own and the other variable. As Arellano & Bover (1995) proposes, this study uses forward orthogonal deviations (FOD) in its estimation technique to minimize data loss (Abrigo & Love, 2016: 780).

Before applying GMM panel VAR analysis, it is necessary to determine the optimal lag length (m) based on the criterion Andrews & Lu (2001) proposed. According to this study, the lag length selection criterion is based upon model and moment selection criteria (MMSC) for GMM estimation. MMSC depends on the coefficient of determination (CD), Hansen's J statistic, and minimisation of modified Bayesian Information Criteria (MBIC), modified Akaike Information Criteria (MAIC), and modified Hannan Quinn Information

Criteria (MQIC). Hansen's J statistic is used to test over-identifying restrictions. Among the lag lengths with valid over-identifying restrictions, the one which minimises MAIC, MBIC, and MQIC is chosen as the optimal lag length (Yerdelen-Tatoğlu, 2018: 138-9).

An important step in the panel VAR approach is determining whether the empirical findings are stable. Stability can be checked by examining moduli values in the eigenvalue stability condition. Moduli values smaller than 1 confirm the stability condition. Stability can also be analysed using a graph that visualises the roots of the companion matrix. If all the roots are placed inside the unit circle, the panel VAR findings are accepted as stable. Determining stability is also necessary to generate forecast-error variance decomposition (FEVD) analysis and impulse response functions (IRFs). These two tools are used to track how each variable affects itself and the other variable throughout time. Determining impulse and response variables is crucial to generate IRFs and FEVD to interpret the findings. The findings from the panel Granger-Causality test and the relevant theory must be followed to determine impulse and response variables (Abrigo & Love, 2016: 793-6).

The study applies Panel VAR-Granger Causality Analysis to investigate causality between variables of interest. Equations (3) and (4) present empirical models of the relevant analysis (Yerdelen-Tatoğlu, 2018: 153), which include the variables used in this study.

$$dlnEMP_{it} = \propto_i + \sum_{k=1}^{K} \gamma_k dlnEMP_{it-k} + \sum_{k=1}^{K} \beta_k dlnMFP_{it-k} + \varepsilon_{it} \tag{3}$$

$$dlnEMPY_{it} = \propto_i + \sum_{k=1}^{K} \gamma_k dlnEMPY_{it-k} + \sum_{k=1}^{K} \beta_k dlnMFP_{it-k} + \varepsilon_{it} \tag{4}$$

where, i denotes economies and t denotes the year. α_i is the constant parameter, k is the lag length, and ε is the error term. All the variables are endogenous in equations in 3 and 4, and the equations indicate a dynamic relationship between variables. *lnEMP*, *lnEMPY*, and *lnMFP* are the variables used in this study and they represent natural logarithms of total employment, youth employment, and multifactor productivity, respectively. The variables included in the analysis are not stationary in their first difference and they become stationary in their first difference. Thus, all the variables are used in their first difference in the analysis. (The first differences are shown by the letter 'd' in front of the names of variables.) $\gamma_k$and $\beta_k$are the estimated parameters. The significance of β_k parameter shows that there is causality from MFP to (youth) employment. The causality can also be examined through the Wald test which tests chi-square statistic under the null hypothesis of no Granger-causality. The findings only show whether there is causality from one variable to another. They do not provide information about the magnitude of causality (Yerdelen-Tatoğlu, 2018: 153-4).

4. Empirical Findings

4.1. Testing for Stationarity of Variables

The study first tests the stationarity using panel unit-root rests. To choose between first and second-generation tests, Pesaran-CD (2004) test is applied to investigate the existence of cross-sectional dependence. The findings from this test are presented in Table 3.

Table: 3
Pesaran’s Cross-Sectional Dependence Test, 16 OECD Economies, 1985-2018

Variable	CD-Test	p-value	corr	abs(corr)
lnEMP	46,24	0,000	0,724	0,729
lnEMPY	16,32	0,000	0,256	0,446
lnMFP	52,77	0,000	0,826	0,826

Source: Author’s calculations.
Notes: lnEMP is employment, lnEMPY is youth employment, and lnMFP is multifactor productivity. All the variables are presented in natural logarithms.

The findings from Pesaran-CD (2004) test indicate the rejection of the null of cross-sectional independence. Because all the variables are cross-sectionally dependent, the study applies second-generation panel unit-root tests to test for the stationarity of variables. Table 4 presents findings from Breitung and Pesaran’s CADF panel unit-root tests.

Table: 4
Breitung and Pesaran’s CADF Panel Unit-Root Tests, 16 OECD Economies, 1985-2018

Variables	Breitung (Lambda statistics)		Pesaran’s CADF (t-bar statistics)	
	C	C+T	C	C+T
lnEMP	4,524	1,663	-2,186*	-2,457
lnEMPY	2,109	2,843	-2,032	-2,041
lnMFP	2,189	1,032	-2,546***	-2,423
dlnEMP	-5,425***	-6,277***	-3,245***	-3,273***
dlnEMPY	-8,547***	-6,385***	-2,744***	-2,815***
dlnMFP	-9,083***	-9,693***	-3,168***	-3,122***

Source: Author’s calculations.
*Note: C denotes model with constant, and C+T denotes model with constant and trend. *, **, *** denotes the rejection of the null hypothesis of non-stationarity (presence of unit root) at the 10%, 5%, and 1% levels, respectively. For Pesaran CADF test, critical values for the models with constant are -2,11, -2,20, and -2,36; with constant and trend are -2,63, -2,71, and -2,85 at the 10%, 5% and 1% levels, respectively.*

Findings in Table 4 indicate that all variables are non-stationary in their level. Two exceptions are the total employment *(lnEMP)* and the MFP *(lnMFP)* according to Pesaran’s CADF test for the model with constant. Because all the other test statistics present the non-stationary of these variables at their level, they are accepted to be non-stationary. The findings from the first difference of the variables (*ΔlnEMP, ΔlnEMPY, and ΔlnMFP)* indicate the rejection of the null hypothesis of the presence of uni-root; thus, non-stationary variables. Because the panel VAR approach and causality analysis can be applied to stationary variables, the rest of this study uses the first differences of all variables: *dlnEMP*, *dlnEMPY*, and *dlnMFP* to apply the relevant methodologies.

4.2. GMM Panel VAR Approach

The first step to apply the GMM Panel VAR Approach is determining the optimal lag length for the analysis. Table 5 shows the estimated coefficient of determination (CD), Hansen’s J statistics, p-values for Hansen’s J statistics, MBIC, MAIC, and MQIC. As the study investigates the employment and MFP nexus separately for total and youth employment, findings from the two models are presented independently. The upper part of

Table 5 presents findings for optimal lag length for the total employment model, whereas the below part shows the findings from the youth employment model.

Table: 5
Determining Optimal Lag Length, 16 OECD Economies, 1985-2018

Employment, MFP						
lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0,5417	11,3165	0,7895	-83,2129	-20,6835	-45,5258
2	0,5218	5,8164	0,9251	-65,0806	-18,1836	-36,8153
3	-0,0261	3,8471	0,8707	-43,4176	-12,1529	-24,5740
4	27,4944	0,9472	0,9177	-22,6851	-7,0528	-13,2633
Youth Employment, MFP						
lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0,2449	13,9179	0,6048	-80,6114	-18,0821	-42,9244
2	0,2929	6,8678	0,8662	-64,0292	-17,1322	-35,7639
3	-9,8143	1,3313	0,9952	-45,9334	-14,6688	-27,0899
4	-30,8507	0,3837	0,9838	-23,2486	-7,6163	-13,8269

Source: Author’s calculations.

According to findings from Hansen’s J statistics and p-values for J statistics in Table 5, the null hypothesis of the validity of over-identifying restrictions is not rejected. The lag length that minimises MBIC, MAIC, and MQIC is lag 1 for both employment and youth employment models. Thus, the optimal lag length is selected as 1 lag for both models.

Table 6 presents GMM Panel VAR Analysis findings for total employment and youth employment models with 1 lag. Table 6 shows that the lagged MFP variable significantly and positively affected total employment, whereas the lagged employment variable did not significantly affect the MFP variable during the period examined. In addition, the lagged variables significantly and positively affect their current values. Empirical findings from the youth employment model indicate that the lagged value of MFP significantly and positively affects youth employment; however, the impact of lagged youth employment on MFP is significant, negative, and relatively low. Youth employment and MFP are significantly and positively affected by their lagged values. These findings show that although MFP leads to an increase in total and youth employment, youth employment leads to a decline in MFP, and total employment does not significantly affect MFP.

Table: 6
Findings from GMM Panel VAR Analysis, 16 OECD Economies, 1985-2018

Employment, MFP			Youth Employment, MFP	
	Coefficient [Std. Error]			Coefficient [Std. Error]
dlnEMP			*dlnEMPY*	
$dlnEMP_{t-1}$	0,3792*** [0,0956]		$dlnEMPY_{t-1}$	0,5866*** [0,0698]
$dlnMFP_{t-1}$	0,2223*** [0,0599]		$dlnMFP_{t-1}$	0,3130** [0,1304]
dlnMFP			*dlnMFP*	
$dlnEMP_{t-1}$	-0,0420 [0,0357]		$dlnEMPY_{t-1}$	-0,0683*** [0,0169]
$dlnMFP_{t-1}$	0,2878*** [0,0654]		$dlnMFP_{t-1}$	0,2923*** [0,0639]

Source: Author’s calculations.
*Notes: lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and MFP, respectively. d presents the first differences, and t-1 denotes the first lag of variables. Standard errors are in brackets. *, **, *** denotes the significance of the coefficients at the 10%, 5%, and 1% levels, respectively. The optimal lag length is 1.*

4.3. Causality Analysis

After examining the dynamic relationship between variables of interest through the GMM Panel VAR approach, the study applies the panel Granger Causality test to determine whether variables of interest Granger cause each other. Table 7 presents findings from Panel VAR-Granger Causality Wald Test.

Table: 7
Findings from Panel VAR-Granger Causality Wald Test, 16 OECD Economies, 1985-2018

Equation	Excluded	Chi-square	Equation	Excluded	Chi-square
dlnEMP	dlnMFP	13,749***	*dlnEMP_Y*	dlnMFP	5,763**
	ALL	13,749***		ALL	5,763**
dlnMFP	dlnEMP	1,382	*dlnMFP*	dlnEMP_Y	16,262***
	ALL	1,382		ALL	16,262***

Source: Author’s calculations.
*Notes: Findings are based on Panel VAR analysis with 1 lag. lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and MFP, respectively. d presents the first differences of variables. *, **, *** denotes rejection of null of the excluded variables does not Granger-cause the equation variable at the 10%, 5%, and 1% levels, respectively.*

Empirical findings in Table 7 show that MFP Granger-caused employment and youth employment, while only youth employment Granger-caused MFP over the period examined. Total employment did not Granger-cause MFP. Thus, even though the past values of MFP were beneficial in predicting total and youth employment levels, the reverse causality was valid only for youth employment. The findings indicate a two-way causality between youth employment and MFP and a one-way causality from MFP to total employment. These findings are summarised as follows:

Employment $\leftarrow$ MFP

Youth Employment $\leftrightarrow$ MFP

4.4. Stability of the Findings

It is necessary to test models' stability in panel VAR analyses. The stability test also serves as a necessary step to generate IRFs and FEVD. Table 8 presents findings from the eigenvalue stability condition, and Figure 2 shows the roots of the companion matrices.

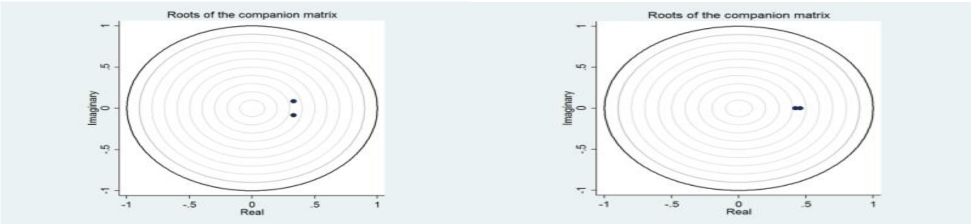
Table: 8
Eigenvalue Stability Condition, 16 OECD Economies, 1985-2018

Employment, MFP			Youth Employment, MFP		
Eigenvalue		Modulus	Eigenvalue		Modulus
Real	Imaginary		Real	Imaginary	
0,3335	0,0850	0,3441	0,4563042	0	0,4563
0,3335	-0,0850	0,3441	0,4226	0	0,4226

Source: Author's calculations.

Table 8 shows that modulus values are smaller than one. Thus, panel VAR models of interest are stable.

Figure: 2
Roots of the Companion Matrices, 16 OECD Economies, 1985-2018



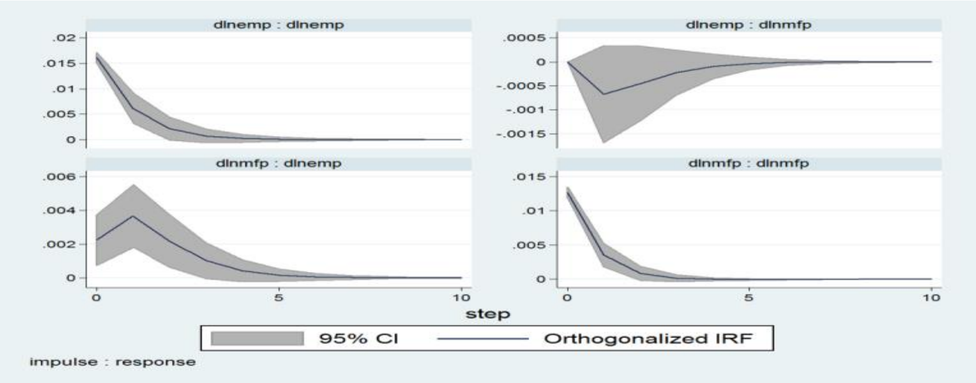
Source: Author's calculations.
Notes: Matrix for total employment on the left and youth employment on the right.

Figure 2 shows that all the roots are inside the unit circle and smaller than 1. These findings confirm the stability of panel VAR models.

4.5. Impulse Response Functions and Forecast-Error Variance Decomposition

After confirming the stability of panel VAR models using eigenvalue stability conditions and companion matrices, IRFs and FEVD can now be generated. Considering the theoretical considerations and findings from the panel Granger Causality test, this study generates IRF and FEVD to represent the impact (impulse) of MFP on employment measures (response). Figures 3 and 4 indicate IRFs for MFP and total employment and MFP and youth employment models, respectively. Table 9 presents FEVD for both models. 95% Confidence intervals were generated using 200 Monte Carlo simulations from the panel VAR findings.

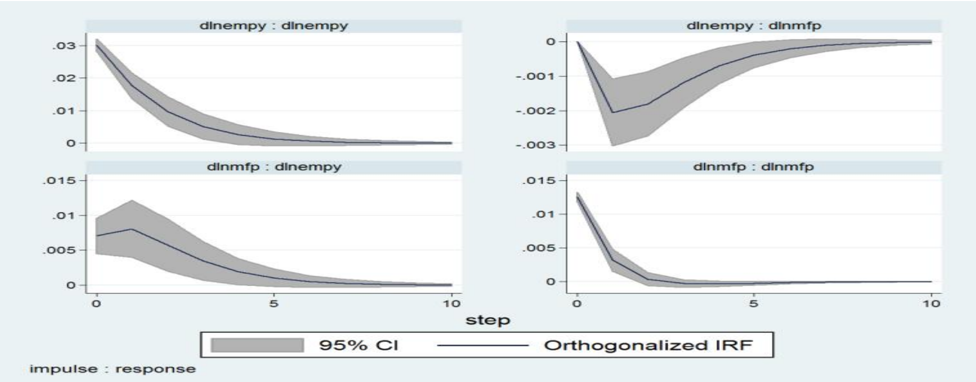
Figure: 3
Impulse Response Functions (IRFs) for MFP and Employment, 16 OECD Economies, 1985-2018



Source: Author's calculations.
Notes: Findings are based on Panel VAR analysis. lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and MFP, respectively. d presents the first differences in variables.

The top-right panel in Figure 3 shows that lagged total employment (*dlnEMP*) did not significantly affect MFP (*dlnMFP*) because the confidence intervals contain all parts of the zero line. On the other hand, the impact of MFP (*dlnMFP*) was significant, as presented in the bottom left panel in Figure 3. MFP resulted in a positive effect on total employment. Such impact was the highest in the second period, declined afterwards, and disappeared in 6-7 years.

Figure: 4
Impulse Response Functions (IRFs) for MFP and Youth Employment, 16 OECD Economies, 1985-2018



Source: Author's calculations.
Notes: Findings are based on Panel VAR analysis. lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and MFP, respectively. d presents the first differences of variables.

Figure 4 indicates that youth employment and MFP variables significantly affected each other. The top-right panel shows a negative impact of lagged youth employment on MFP to be disappeared in 8-9 years. The impulse of MFP on youth employment can be tracked in the bottom-left panel in Figure 4, and it presented a positive impact that disappeared in 8-9 years. The IRFs in Figures 5 and 6 confirm the findings from the panel VAR approach and panel VAR Granger Causality tests.

Table: 9
Forecast-Error Variance Decomposition, 16 OECD Economies, 1985-2018

(a) MFP, Employment				(b) MFP, Youth Employment		
Response variable and forecast horizon	Impulse Variable			Response variable and forecast horizon	Impulse Variable	
	dlnmfp	dlnemp			dlnmfp	dlnempy
dlnmfp				dlnmfp		
0	0	0		0	0	0
1	1	0		1	1	0
2	0,997369	0,002631		2	0,9755	0,0245
3	0,996219	0,003781		3	0,957418	0,042582
4	0,995942	0,004058		4	0,949775	0,050225
5	0,995892	0,004108		5	0,947199	0,052801
6	0,995884	0,004116		6	0,946429	0,053571
7	0,995883	0,004117		7	0,946215	0,053785
8	0,995883	0,004117		8	0,946159	0,053841
9	0,995883	0,004117		9	0,946145	0,053855
10	0,995883	0,004117		10	0,946142	0,053858
dlnemp				dlnempy		
0	0	0		0	0	0
1	0,018942	0,981058		1	0,052267	0,947733
2	0,058443	0,941557		2	0,086451	0,913549
3	0,071349	0,928651		3	0,101459	0,898541
4	0,074189	0,925811		4	0,106955	0,893045
5	0,074681	0,925319		5	0,108726	0,891274
6	0,074753	0,925247		6	0,109246	0,890754
7	0,074762	0,925238		7	0,109388	0,890612
8	0,074763	0,925237		8	0,109425	0,890575
9	0,074763	0,925237		9	0,109435	0,890565
10	0,074763	0,925237		10	0,109437	0,890563

Source: Author's calculations.
Notes: Findings are based on Panel VAR analysis. lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and MFP, respectively. d presents the first differences of variables.

FEVD in Table 9 shows how much of the forecast-error variance (FEV) in variables was determined by themselves and the other variable of interest. Panel (a) indicates the findings for MFP and total employment overall, and panel (b) indicates the findings for MFP and youth employment model. 0 values of MFP in the 0-time horizons in the bottom part of both panels show that FEVD findings were generated by the impact of MFP on employment variables. 0 values of employment variables can also confirm the ordering of the relevant relationship in the 1-time horizons in the upper part of both panels. These 0 values indicate that the impacts of MFP on employment variables were investigated concurrently, whereas the reverse impacts were examined with a one-period lag.

The bottom part of the panel (a) in Table 9 indicates that 92.5% of FEV of total employment (*dlnEMP*) was explained by the shocks in itself, and 7.5% of the FEV was explained by the MFP (*dlnMFP*) on the tenth lag. On the other hand, panel (b) shows the relevant values for youth employment. Approximately 89.1% of the FEV shocks of youth employment (*dlnEMPY*) could be determined by itself, and 11% of such shocks could be determined by the MFP (*dlnMFP*). Lastly, panel (b) showed that 94.6% of the FEV of MFP (*dlnMFP*) was explained by self-shocks, and 5.4% of it was explained by the shocks in youth employment (*dlnEMPY*) variable. Table 9 shows that MFP resulted in more significant shocks in FEV on youth employment than it did in total employment over the period examined.

5. Discussion of the Empirical Findings and Policy Recommendations

Discussion of the empirical findings of this study focus on two different issues. The first issue focuses on the potential reasons why macro-level studies on the topic - including this study - reach different findings in the empirical literature. Even though there is only a limited number of empirical macro studies, the literature evidence mixed outcomes. The primary reason may be the selection of countries and periods in different studies. Aside from this, one reason may depend on the choice of proxy for technological change variable among many other proxies, as Piva & Vivarelli (2017: 13) points out. The relevant proxy used in this study is MFP, which presents technology's network and spillover effects (OECD, 2020d). Thus, the insignificant total employment parameter on MFP can be understood as newly-created jobs do not contribute to technological progress through network and spillover effects. The insufficiency of total employment to contribute to technological progress will be addressed in a more detailed manner during the discussion of the second issue.

The second issue requires an in-depth understanding of the empirical findings reached in this study. To put together, the findings in this study point out a job-creation effect of MFP for both total and youth employment. However, the inverse of this relationship is not confirmed in this study. Total employment cannot contribute to technology creation in the countries examined. In addition, while youth employment generates a change in technological level, this level is evidenced to be negative. In other words, higher youth employment leads to a decline in technological change. These findings on the mutual relationship between employment and technological change in this study require attention because these two variables are expected to affect each other mutually. While higher technological level creates changes in the labour market, it is evident and well-known in the literature that labour also contributes to knowledge and technology creation. For the study sample, even though technological change creates jobs, these jobs cannot contribute to the technological progress through the network and spillover effects in these 16 OECD economies over the period examined. Considering that most of the economies in the analysis are from developed economies - OECD members - the examination of the reason(s) for these empirical findings becomes even more necessary for further consideration. A discussion on the topic is needed from this perspective.

To better understand why total employment does not lead to technological progress, one can focus on the choice of proxy for technological change, as this issue was briefly introduced at the beginning of this section. As this study uses MFP, the study finds out that total employment in the 16 OECD economies cannot significantly affect the MFP level. The MFP variable in this study refers to "the network and spillover effects from production factors", as explained by the source of the relevant dataset of OECD (OECD, 2020d). Thus, the insufficiency of employment to create or activate spillover effects may, at least partially, stem from structural issues related to the labour market, such as job-skill mismatch. Even though the countries that constitute the study sample are from OECD economies and these economies are well-known for their highly skilled labour force, the market forces do not always guarantee the most suitable job-skill match for labour supply and labour demand. Job-skill mismatch occurs when an employed person's skills or education are not in line with the required task of the job. Accordingly, examining the job-skill mismatch for the study sample can explain why total employment remains insufficient to create technological progress in these 16 OECD economies. Table 10 shows field-of-study-mismatch and qualification mismatch for all the countries included in the empirical analysis except Japan.

Table: 10
Job-Skill Mismatch, 15 OECD Economies, 2016

Country	Field-of-study mismatch (%)	Qualification mismatch (%)	Qualification mismatch	
			Under-qualification (%)	Over-qualification (%)
Australia	32,7	38,7	18,5	20,2
Belgium	28	34,5	23,8	10,6
Canada		37,9	21,7	16,2
Denmark	30,8	34	20	14
Finland	23,7	28,2	20,3	7,8
France	33,4	34,2	23,5	10,6
Germany	20,1	37,2	19,7	17,2
Italy	36,5	38,2	20	18,2
Netherlands	33,2	37,7	25,1	12,6
New Zealand		40,7	23,5	17,2
Portugal	35,9	42,4	18,7	23,6
Spain	33,7	41,2	21,2	20
Sweden	35,4	37	22,3	14,6
United Kingdom	38	41	27,7	13,5
United States		33,5	17,7	15,6

Source: OECD, 2022.
Notes: The values in the table represent percentages of the total number of workers.

Job-skill mismatch statistics in Table 10 clearly show that more than one-third of workers in all economies other than Finland report qualification mismatch, meaning that their skills do not match the required skill of their job. Table 10 also reports data on under-qualification, over-qualification, and field-of-study mismatch. Over-qualification occurs when a worker has higher skills than the tasks required in a job, and under-qualification occurs in the opposite situation. In most of these economies, it is evident that under-qualification is a more critical issue compared to over-qualification. Field-of-study mismatch statistics are similar yet slightly lower than qualification mismatch statistics. Considering the development levels and human capital accumulation in these economies, it is clear that mismatch - particularly field-of-study mismatch and under-qualification - is an important issue for the study sample. Such a matter requires not only further analyses but also policy recommendations. Because the endowed skills are mainly acquired through education, the most critical policy recommendation would be directed to the educational structure in these economies. After assessing the necessities of labour demand in these economies, the required jobs contributing to technological advancement should be determined. Following that, necessary educational programs should be activated or increased to ensure sufficient employed persons to build future labour supply. Another policy recommendation would be making revisions in education programs, if necessary.

Undoubtedly, the job-skill mismatch can be only one factor that shapes the labour market structure. Thus, further research would be necessary to understand why total employment cannot contribute to the technology creation process in these economies. Future research can address the interconnection between technological progress and factors that build the labour market structure in the OECD economies.

Even though the mismatch data is only announced for total workers, the job-skill mismatch can be an important issue, particularly for the youth. It is well-known that youth generally face more difficulty finding a job than adults (Signorelli, 2017: 1), mainly if they are newly graduates. Keeping their jobs is riskier for the youth during crisis periods because they are less experienced than adults. In addition, young workers frequently get lower wages, are offered part-time jobs and/or temporary contracts, and may face more precarious work conditions. Because of their vulnerability in the labour market, they usually accept to be employed in jobs that do not fit their qualities or field-of-study, rather than remaining unemployed (Dunsch, 2017: 378; Gorkey, 2020: 4). Such job-skill mismatch may create disadvantages for youth employment to a more significant extent for generating technological progress. This reason may, at least partially, explain the negative impact of youth employment of MFP, as empirically evidenced in this study. Thus, some policy actions can be recommended in this manner. First, it would be beneficial to determine the level of both field-of-study and qualification mismatch specifically for the youth in the 16 OECD economies included in this study. After determining the level of a mismatch for the youth, either revision in study programs can be made, or these programs can be increased in numbers, depending on the necessity. Active labour market policies specifically for the youth can also be worthwhile. Such policies can offer more extensive employment opportunities for the youth while they can help to decrease the extent of mismatch at the same time.

Finally, future research directions can be offered based on the empirical findings obtained and the discussion held in this study. Further research can be suggested to examine the technological change and employment nexus by distinguishing technological change from its different proxies. Another future research can focus on determining the country-specific structural labour market problems and examining the relationship between these problems and technological progress. The last future research direction can discuss the technological progress and youth employment by skill structure.

6. Conclusion

This study investigates the dynamic relationship and causality between employment and technological change by distinguishing employment by youth employment and total employment in 16 OECD economies from 1985 to 2018. It aims to reveal whether the relevant mutual relationship is different for youth employment compared to the total. It uses MFP as a proxy for technological change.

This study finds that the dynamic relationship and the causality between employment and technological change are different for the youth than for total employment. The findings from GMM Panel VAR approach estimates indicate a significant and positive impact of MFP on total employment; however, the inverse of such relationship yields an insignificant effect. On the other hand, the results show that youth employment and MFP significantly affect each other. While MFP affects youth employment positively, the impact of youth employment on MFP is evidenced negatively. The findings from the Granger-causality analysis confirm panel VAR estimates. There is a one-way causality from MFP to employment and a two-way causality between MFP and youth employment. The eigenvalues and roots of companion matrices confirm the stability of the empirical findings. Findings from IRFs and FEVDs show parallelism with panel VAR and causality estimates. IRFs indicate an insignificant lagged effect of MFP on total employment and a significant positive effect of total employment on MFP that disappears in 6-7 years.

On the other hand, IRFs confirm a two-way relationship on the nexus for the youth. While the impact of MFP on youth employment is positive, youth employment results in a decline in MFP with a one-year time lag. Both effects disappear in 8-9 years. Thus, the empirical findings show that technological change affects youth employment at a higher magnitude and more extended period than total employment.

The findings from the empirical evidence of this study are crucial as they signal some critical issues on the matter. First of all, the findings indicate the job-creation effect of technological change for both total and youth employment in the selected OECD economies during the period examined. However, the inverse relationship is not significant for total employment. In other words, even though technological change creates jobs, the employed persons in these jobs cannot lead to an increase in technological level. While total employment does not significantly affect the technological level, youth employment negatively affects the technological level. Thus, the second important issue empirically evidenced in this study is that higher youth employment results in decline in MFP. The incapability of total and youth employment to increase MFP may arise for different reasons. One of the reasons is that other studies may find different empirical outcomes depending on the proxy they choose for their technological change variable, as Piva & Vivarelli (2017: 13) point out. This may be considered one of the most important reasons for mixed findings in the macro empirical literature on the topic. The technological change variable used in this study is MFP, which presents technology's network and spillover effects (OECD, 2020d). Thus, the insignificant total employment parameter on MFP can be understood as newly created jobs cannot generate technological change through network and spillover effects. Another reason behind the two important issues may be a job-skill mismatch, particularly for the youth. In addition to their vulnerability in the labour markets, young individuals generally face more difficulty finding a job than adults (Signorelli, 2017: 1), mainly if they are newly graduates. Because of these difficulties and the limited number of job opportunities, they may choose to work in jobs that do not fit their qualifications well rather than remain unemployed. Therefore, the job-skill mismatch can be regarded as a more important problem for the youth, even in developed economies.

By empirically evidencing distinct outcomes on the technological change and employment nexus for the youth and total employment, this study does not only suggest future research directions but also policy recommendations. Future research attempts can be directed to distinguishing the analysis by skill structure, different proxies for technological change, and examining the relevant nexus focusing on various structural labour market problems. Such examination and the comparison of findings from these future research directions and the present study would be beneficial to provide a better understanding of the technological change-employment nexus. Policy recommendations on the issue mainly include actions that aim to reduce the mismatch in these economies. For this purpose, particular policies, such as revisions in study programs and increasing the number of programs that can fulfil the requirements of labour demand, are offered. Finally, the implementation of active labour market policies is suggested as these policies increase the employment opportunities for the youth so that young individuals can match with jobs that correspond to their educational background and skills in a better way.

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Appendix A. Summary Statistics by Economies

Table: A.1.
Summary Statistics by Economies, 1985-2018

Economy	*Variable*	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
Austria	*lnEMP*	34	9,133	0,184	8,809	9,440
	lnEMPY	34	7,948	0,094	7,818	8,139
	lnMFP	34	4,516	0,077	4,393	4,613
Belgium	*lnEMP*	34	8,310	0,095	8,165	8,467
	lnEMPY	34	6,828	0,086	6,732	6,996
	lnMFP	34	4,562	0,047	4,441	4,614
Canada	*lnEMP*	34	9,615	0,144	9,361	9,834
	lnEMPY	34	8,326	0,071	8,191	8,416
	lnMFP	34	4,540	0,059	4,446	4,626
Denmark	*lnEMP*	34	7,895	0,027	7,839	7,949
	lnEMPY	34	6,546	0,118	6,369	6,744
	lnMFP	34	4,549	0,053	4,445	4,642
Finland	*lnEMP*	34	7,768	0,061	7,623	7,840
	lnEMPY	34	6,294	0,125	6,084	6,542
	lnMFP	34	4,489	0,145	4,214	4,657
France	*lnEMP*	34	10,096	0,074	9,958	10,206
	lnEMPY	34	8,626	0,107	8,498	8,838
	lnMFP	34	4,546	0,068	4,399	4,629
Germany	*lnEMP*	34	10,517	0,064	10,385	10,643
	lnEMPY	34	9,026	0,105	8,849	9,300
	lnMFP	34	4,506	0,093	4,312	4,630
Italy	*lnEMP*	34	9,980	0,050	9,896	10,053
	lnEMPY	34	8,322	0,265	7,871	8,688
	lnMFP	34	4,619	0,036	4,535	4,676
Japan	*lnEMP*	34	11,056	0,031	10,969	11,107
	lnEMPY	34	9,456	0,143	9,243	9,645
	lnMFP	34	4,515	0,076	4,330	4,620
Netherlands	*lnEMP*	34	8,906	0,150	8,542	9,082
	lnEMPY	34	7,664	0,058	7,487	7,737
	lnMFP	34	4,550	0,064	4,428	4,623
New Zealand	*lnEMP*	34	7,545	0,176	7,192	7,863
	lnEMPY	34	6,287	0,091	6,181	6,491
	lnMFP	34	4,542	0,061	4,379	4,610
Portugal	*lnEMP*	34	8,449	0,071	8,308	8,546
	lnEMPY	34	6,940	0,256	6,467	7,225
	lnMFP	34	4,590	0,056	4,396	4,631
Spain	*lnEMP*	34	9,645	0,203	9,297	9,932
	lnEMPY	34	8,187	0,227	7,769	8,501
	lnMFP	34	4,595	0,020	4,538	4,624
Sweden	*lnEMP*	34	8,387	0,071	8,274	8,536
	lnEMPY	34	6,882	0,126	6,704	7,115
	lnMFP	34	4,494	0,086	4,375	4,605
UK	*lnEMP*	34	10,230	0,082	10,096	10,384
	lnEMPY	34	8,912	0,079	8,835	9,109
	lnMFP	34	4,506	0,103	4,320	4,621
US	*lnEMP*	34	11,795	0,103	11,582	11,956
	lnEMPY	34	10,459	0,039	10,389	10,525
	lnMFP	34	4,491	0,096	4,340	4,621

Source: Author's calculations.
Notes: lnEMP, lnEMPY, and lnMFP are the natural logarithms of employment, youth employment, and multifactor productivity, respectively.