

INSIGHTS INTO LABOUR AND ECONOMIC DYNAMICS IN OECD COUNTRIES: A NON-PARAMETRIC CAUSAL ANALYSIS USING TRANSFER ENTROPY

*(Penelitian tentang Dinamik antara Guna Tenaga dan Ekonomi di Negara OECD:
Analisis Kausal Tidak Berparameter Menggunakan Pindahan Entropi)*

NUR LAYALI MOHD ALI KHAN* & SAIFUL IZZUAN HUSSAIN

ABSTRACT

The eighth goal of the global sustainable development agenda emphasises the role of the labour market as a driver of economic growth. However, the complex relationships between these elements still need to be discussed. In this study, a novel approach, called transfer entropy, is applied to analyse the causal relationships between real gross domestic product (GDP), employment, and unemployment across 38 OECD countries spanning the period of the third quarter of 2011 to the second quarter of 2023. A rigorous transfer entropy framework allows us to examine the directional flow of information between three pairs of variables: real GDP and employment, real GDP and unemployment, and employment and unemployment. The study shows that the causal relationships vary across OECD countries. The results from 38 OECD member countries improve the understanding of the reciprocal relationship between labour and output and discuss the role of fiscal and monetary policy in these cycles. The study contributes to the existing literature by offering a distribution-free statistical analysis approach to examine causality in real data and provide guidance to policymakers and businesses in designing strategic policies for sustainable economic development at national and regional levels.

Keywords: transfer entropy; causality; labour market; employment; unemployment; economic growth

ABSTRAK

Matlamat kelapan yang digariskan dalam agenda global pembangunan lestari memberi penekanan kepada peranan pasaran buruh untuk memacu pertumbuhan ekonomi. Namun, hubungan yang kompleks antara elemen ini memerlukan penelitian lanjut. Kajian ini menggunakan pendekatan baharu yang dikenali sebagai pindahan entropi bagi menganalisis hubungan kausal antara keluaran dalam negeri kasar (KDNK), guna tenaga dan pengangguran di 38 buah negara OECD bagi tempoh suku ketiga 2011 sehingga suku kedua 2023. Kerangka kerja pindahan entropi yang terperinci menyediakan asas bagi mengkaji arah aliran maklumat antara tiga pasangan pemboleh ubah: KDNK benar dan guna tenaga, KDNK benar dan pengangguran, dan guna tenaga dan pengangguran. Kajian menemukan kepelbagaian hubungan kausal bagi negara-negara OECD. Dapatan kajian daripada 38 negara anggota OECD meningkatkan kefahaman hubungan timbal balik antara buruh dan output serta membincangkan peranan dasar fiskal dan monetari dalam kitaran ini. Kajian ini menyumbang kepada literatur sedia ada dengan mengetengahkan pendekatan analisis statistik bebas taburan bagi meneliti hubungan kausal dalam data sebenar dan memberi panduan kepada penggubal dasar dan entiti perniagaan untuk merangka dasar strategik ke arah pertumbuhan ekonomi yang mampan di peringkat nasional dan serantau.

Kata kunci: pindahan entropi; kausal; pasaran buruh; guna tenaga; pengangguran; pertumbuhan ekonomi

1. Introduction

The relationship between labour market conditions and economic development is a topic of great interest given the fundamental role of labour in economic production (Kaufman & Hotchkiss 2006; Stiglitz *et al.* 2016). The all-encompassing global Sustainable Development Goals (SDG) agenda attaches great importance to the labour market through the monitoring of 14 indicators included in five of the 17 goals (International Labour Organization 2018). In particular, the labour market is linked to economic growth through SDG 8 on promoting inclusive and sustainable economic growth, employment, and decent work (International Labour Organization 2018; Lee *et al.* 2020; United Nations Department of Economic and Social Affairs 2023). Therefore, a precise understanding of labour market dynamics is crucial for assessing the economic development of a country, region or area.

A well-functioning labour market supports economic growth through the effective utilisation of human capital in productive economies, while economic development influences labour demand, stimulates job creation, and impacts wage levels (Borjas 2016; Kaufman & Hotchkiss 2006; Stiglitz *et al.* 2016). A high level of employment contributes to elevated household income, increased consumption, and better standards of living, thereby reinforcing economic expansion (Ana Lugo 2007; Borjas 2016; Mankiw 2021). On the contrary, high unemployment level leads to diminished income, lower consumption, and reduced economic output, hence widening income disparities (Borjas 2016; Junankar 2016; Mankiw 2021; McConnell *et al.* 2016). The interconnectedness between the labour market and economic development is critical to economic stability, income distribution, and overall well-being. Thus, thorough grasp of this relationship facilitate the formulation of effective labour market policies that support sustainable and inclusive economic growth.

Real gross domestic product (GDP) is an official and widely accepted measure used by countries to assess the size and growth of an economy (Greenlaw & Shapiro 2017; Lee *et al.* 2019; Stiglitz *et al.* 2016). This important economic indicator measures the total goods and services produced within a geographically confined boundary of a country to gauge the progress of an economy at a macro level (van der Bergh 2009; Landefeld 2000; Mankiw 2021; Stiglitz *et al.* 2016). Employment, which serves as a broad indicator of labour utilisation, refers to individuals engaged in an activity that produces goods or services for remuneration or profit (International Labour Organization 2023). Employment is also associated with the livelihood and well-being of individuals (Ana Lugo 2007; Apablaza *et al.* 2023). On the other hand, unemployment, one of the indicators of labour underutilisation, is the segment of the labour force that is actively looking for a job but cannot find employment for various reasons (International Labour Organization 2013). Accurate interpretations of these indicators are essential to assess labour force utilisation and economic performance in different regions.

The demand in the labour market is fundamentally derived from aggregate demand in the economy as a whole. In response to the increased demand for goods and services, firms expand their business activities and create jobs. This employment provides individuals with income, boosting household consumption and further contributing to aggregate demand. In contrast, the fall in aggregate demand below the required level to maintain production can lead to layoffs and a decline in hiring, resulting in demand-deficient unemployment (Mankiw 2021; McConnell *et al.* 2016). Job losses and reduction in employment opportunities reduce households' disposable income, leading to lower consumption, further weakening overall demand and creating a negative feedback loop that can cause an additional decrease in real GDP. This circumstance makes it particularly important to understand the interactions between the labour force and the economy across different geographical areas and stages of development. The focus on employment, unemployment, and GDP offers a labour-centric perspective on economic development to complement the broader macroeconomic analyses.

In this regard, the Organisation for Economic Co-operation and Development (OECD) presents an interesting context for such analysis. The OECD comprises a diverse group of advanced and emerging economies with a set of shared policy frameworks and best practises that provide fair opportunities in creating wealth and fostering well-being (Organisation for Economic Co-operation and Development 2024c). Together, these economies contribute nearly 65 per cent of global GDP (World Bank 2023a), offering a unique perspective to examine the variability of labour market and economic responses across different stages of development (De La Fuente-Mella *et al.* 2020). This study uses transfer entropy as a robust method to identify causal relationships between employment, unemployment, and real GDP in 38 OECD member countries, providing a nuanced understanding of the labour market and economic dynamics in these economies.

The link between the labour market and the economy has gained prominence in recent research, reflecting its importance for economic policy and sustainable development. However, these studies differ in the selection of labour market and economic variables, the geographical and temporal scope, and the methods used. For instance, Amor (2023) applied an augmented autoregressive distributed lag (ARDL) model to Tunisian time series data from 1980 to 2000 to find cointegration between real GDP growth and unemployment rate, where a one per cent increase in GDP led to approximately a 1.6 per cent decrease in unemployment. Eshun *et al.* (2023) found that labour market flexibility and economic growth in a group of 37 African countries moved in the same direction after applying the Driscoll-Kraay fixed effects estimator and two-step system generalised method of moments (GMM) techniques to time series data between 2000 and 2019. Meanwhile, a cointegration analysis was conducted by Przekota *et al.* (2023) to determine the long-run relationship between real GDP growth and the ratio of labour compensation to nominal GDP for OECD member countries based on time series data from 2003 to 2021. This study found that a higher share of labour compensation in GDP led to slower economic growth, while the rise in GDP influenced an increase in future labour compensation. Although the techniques used in these studies can identify long-run relationships, their assumptions of linearity often hinder the assessment of complex underlying non-linear patterns between the labour market and the economy. In addition, the application of econometric methods to determine causal interactions can lead to endogeneity bias, further limiting the ability to establish true causality between the variables of interest (Antonakis *et al.* 2014; Roberts & Whited 2013). To address these constraints, transfer entropy, a model-free approach originating from information theory, provides a more flexible and robust approach to identifying causal relationships between two or more time series by quantifying the flow of information between these variables (Behrendt *et al.* 2019; Duan *et al.* 2013; Hmamouche 2020). This method is particularly suitable for analysing non-linear and asymmetric relationships (Schreiber 2000; Vicente *et al.* 2011), making it a powerful tool for understanding complex interactions between the labour market and the economy.

Therefore, this study uses transfer entropy analysis to investigate the causality between the labour market and economic development in OECD member countries. By assessing the relationship between the components of the labour force (employment and unemployment) and the economy, this study provides insights into the direction and strength of their interactions. The application of transfer entropy to individual countries' panel data not only contributes to existing literature but also allows for a country-specific examination of the dynamic between the labour market and economic growth. Our analysis reveals diverse causal relationships between real GDP, employment, and unemployment across OECD member countries. The varying strength of the unidirectional and bidirectional causal relationships across countries highlights the complex relationships between economic performance and labour market outcomes. A deeper understanding of these linkages brings more nuanced perspectives, thus enabling policymakers to tailor strategies that foster economic growth, promote employment

opportunities, and reduce unemployment, thereby contributing to the overarching goal of sustainable development. The results of this study underline the need for targeted interventions that align economic policy with labour market dynamics while balancing both the demand-side drivers of growth and the importance of stable and inclusive development strategies.

This paper consists of five sections, including this introductory section. The remaining sections of this paper are organised as follows: The next section reviews the existing literature on the relationship between employment, unemployment, and economic growth, the methods used to study this relationship, and the growing application of transfer entropy in various fields. The third section examines the materials and methods used to assess the relationship between the economy and the labour market for OECD member countries. The fourth section begins with the empirical findings of this study, discusses the similarities and differences of these findings with the previous literature, and draws insights into the policy designs and implications. Finally, the fifth section presents the conclusions of this study and provides an outlook for future research in this area.

2. Literature Review

A growing body of literature has examined the complex relationship between the labour market and the economy. In particular, these studies examined the influence of labour market conditions and economic performance on each other. The labour market is a platform that mediates the exchange of services and compensations between workers and firms (Borjas 2016; Kaufman & Hotchkiss 2006; McConnell *et al.* 2016; Stiglitz *et al.* 2016). This exchange occurs in a cycle of supply and demand between households and firms, with the former making their labour available to the latter in exchange for an agreed wage rate. Expanding on neoclassical labour market theory, the changes in economic situation has a substantial influence towards the labour market behaviour, especially the labour supply (Borjas 2016; Kaufman & Hotchkiss 2006). Meanwhile, Ciegis *et al.* (2013) emphasised the importance of taking labour market changes into account when analysing economic cycles. While these studies acknowledge the dynamic relationship between the labour market and the economy, they hold different views on whether economic trends shape the future of the labour market or vice versa.

Detailed information on the total output of an economy enables an appropriate assessment of the progress of that economy (Lee *et al.* 2019; Stiglitz *et al.* 2016). A comprehensive account aggregating the monetary value of the final production of goods and services for an economy within a given geographic boundary over a given time period yields a measure known as GDP (Mankiw 2021; Stiglitz *et al.* 2016). Despite criticisms over the limitations of GDP in terms of capturing services produced, quality and non-market goods, it remains a widely accepted indicator of national, regional and global economic progress and development (van der Bergh 2009; Jacobs & Šlaus 2010; Lee *et al.* 2019; Stiglitz *et al.* 2016). Given the detailed representation of GDP, the changes in this measure over time, especially in the short term, are an important benchmark for policymakers to assess the business cycle and subsequently prescribe the appropriate policy measures (Feldstein 2017; Gajdosova 2023; Jacobs & Šlaus 2010; Landefeld 2000).

Although labour market circumstances are multifaceted, the core of its operation lies in the cyclical interplay of supply and demand. Borjas (2016) defines the labour supply in an economy as the sum of persons participating in the labour market, comprising the employed and unemployed. The International Labour Organization (2013) stated that the labour force (consisting of the employed and unemployed population) is the supply of labour for the production processes in exchange for some form of remuneration. The general definition of employment is involvement in any activity to produce goods and services for pay or profit within a specific reference period (International Labour Organization 2013; Junankar 2016).

Meanwhile, unemployment is defined as those who are not employed, available for employment, and engaged in all types of activities to seek employment (International Labour Organization 2013; Junankar 2016; Kaufman & Hotchkiss 2006). Since firms' demand for labour is a derived demand motivated by consumers' demand for goods and services, it is crucial to identify the impact of labour supply on the production of goods and services.

In his seminal work, Okun (1962) argued that underutilisation of labour leads to lower economic output. While the study used unemployment as a measure of underutilisation, the reverse can also occur, where a rise in employment can lead to an increase in real output. A study by Tahir *et al.* (2020) found that optimal labour utilisation has a significant impact on economic growth in OECD countries. To determine whether economic growth in Africa is influenced by labour market flexibility in the country, Eshun *et al.* (2023) quantified the latter as a composite index that includes regulations on hiring and firing, minimum wage, wage bargaining and conscription. The study concluded that labour market flexibility has a significantly favourable impact on the economy. These results underline the dynamic relationship between the labour market and the economy in different regions.

Numerous studies have used different methods to measure the interactions between the components of the labour market and the economy. These distinct methodological choices reflect the contextual nature of the relationships, which is characterised by temporal and regional variations. For example, Ciegis *et al.* (2013) used correlation and regression analyses of time series data from 1996 to 2011 to demonstrate that unemployment and job vacancies across European Union (EU) member countries were influenced by GDP. The study found that both variables lagged by one period, with unemployment showing an inverse relationship with GDP, while job vacancies moved in the same direction, indicating their countercyclical and procyclical behaviour respectively (Ciegis *et al.* 2013). Handriyani *et al.* (2018) reported the positive impact of labour force participation rate on economic growth in North Sumatra by applying a two-stage least squares method on time series data from 2006 to 2016. Difference and system GMM were used in time series from 2001 to 2016 to examine the relationship between female labour force participation and economic growth in 79 middle-income countries. This study found that increasing economic growth is crucial for promoting women's participation in the labour market (Yıldırım & Akinci 2021). Although these studies provided valuable results, there is a risk of overlooking non-linear relationships between the labour market and the economy when relying on such methods.

Specific studies have also been conducted extensively to identify the influence of employment and GDP on each other. In separate studies by He (2018) and Meyer and Sanusi (2019), a bidirectional causality was found between employment and economic growth in China and South Africa. He (2018) used the vector autoregressive (VAR) framework to apply Granger causality analysis to time series data spanning the period of 1983 to 2016, while Meyer and Sanusi (2019) applied the VAR model with error correction mechanism (VECM) to quarterly data from the first quarter of 1995 to the fourth quarter of 2016. Unidirectional Granger causality was discovered from GDP to employment in the short run for the United States of America (USA) throughout 1990 to 2019 (Kesici 2022). Colacchio and Vergori (2022) included employment as one of the variables to investigate the impact of economic growth due to tourism activities on the Italian labour market. Their study, which applied panel vector autoregression (PVAR) to data series from 1997 to 2019, also found that economic growth had a positive impact on employment, particularly in the wholesale and retail trade, and accommodation and food services subsectors.

Previous studies on the cause-effect relationship between unemployment and GDP provided contradictory results due to differing methods, data structures and geographical coverage. Özen (2022) discovered a bidirectional causality between the unemployment rate and the GDP growth rate for selected OECD countries when the panel causality test of Dumitrescu and Hurlin

was applied to the time series from 2010 to 2020. However, Shiferaw (2023) found a significant impact of unemployment on GDP in Ethiopia by applying the Toda-Yamamoto causality test to time series data between 1991 and 2021. In addition, the cross-wavelet transform (XWT) analysis also revealed a counter-cyclical relationship between the variables. In contrast, other studies concluded that the change in GDP influenced the unemployment trend. For instance, Altunöz (2024) found a unidirectional causality from economic growth to unemployment in the OECD group of countries, based on a Granger causality analysis for the time series data from 2007 to 2022. Similarly, the Granger causality analysis over the period of 1991 to 2017 showed that real GDP had a significant inverse effect on unemployment in India (Sahoo & Sahoo 2019). Boga (2020) found comparable results for Türkiye after applying a cointegration analysis to the quarterly data series from the first quarter of 2000 to the fourth quarter of 2019. In addition, both studies also established that the surge in real GDP managed to reduce unemployment in the short run but failed to create jobs in the long run (Boga 2020; Sahoo & Sahoo 2019).

Causality analysis, which goes beyond simple correlation, is ideal for identifying the dynamics between the labour market and the economy. From an economic perspective, causality refers to a relationship in which changes in one variable can lead to changes in another (Mankiw 2021; Smith 2015; Stiglitz *et al.* 2016). A key feature of causality that makes it especially useful for time series analysis is temporality, where the cause must take precedence over the effect (Arjas 2012; Eichler 2012). This temporal aspect allows researchers to determine whether historical values of one variable significantly influence the future behaviour of another. Although parametric methods such as correlation, regression, GMM, Granger causality, VAR, VECM, and PVAR are commonly used to explore causal relationships, these approaches often assume linearity or certain modelling structures, which can limit their ability to capture the full complexity and non-linearity inherent in economic systems.

Given the complexity of real labour market and economic data, transfer entropy, a model-free method based on information theory (Behrendt *et al.* 2019; Bossomaier *et al.* 2016; Schreiber 2000; Vicente *et al.* 2011), is introduced as a powerful tool to analyse causal relationships. The concept of mutual information is extended in transfer entropy by focusing not only on the shared information between variables, but also on the directional flow of information over time (Schreiber 2000). Transfer entropy gives insights into dynamic interactions within a complex system by capturing both linear and non-linear dependencies (Bossomaier *et al.* 2016; Hmamouche 2020; Lungarella *et al.* 2007; Vicente *et al.* 2011; Zhang *et al.* 2022).

Since transfer entropy considers temporal events, it is ideal for analysing real-world data where the tendency for relationships to evolve over time is common. According to Barnett *et al.* (2009), Granger causality and transfer entropy provide similar interpretations under the assumption of normally distributed data. However, transfer entropy is particularly attractive as a non-parametric method for analysing causality in non-Gaussian and high-dimensional data, as it works with fewer assumptions about the underlying stochastic process (Behrendt *et al.* 2019; Bossomaier *et al.* 2016; Vicente *et al.* 2011; Wibral *et al.* 2014). In addition, the asymmetric nature of transfer entropy, which enables bidirectional measurement of information flow between two variables, improves its applicability for causal inference (Bossomaier *et al.* 2016; Abdul Razak & Jensen 2014; Schreiber 2000). These advantages make transfer entropy a robust method for identifying causal relationships in real-world data across multiple domains.

Growing bodies of literature demonstrated the application of transfer entropy for causal inferences in diverse fields. This method has been applied to detect the dynamic relationship of variables in a complex system such as industrial processes (Guo *et al.* 2015; Landman & Jämsä-Jounela 2016; Lindner *et al.* 2019; Zhang *et al.* 2022) and neuroscience (Gao *et al.* 2019; Li & Li 2013; Ursino *et al.* 2020; Wibral *et al.* 2014). For example, in the field of industrial process, Lindner *et al.* (2019) found that transfer entropy offers greater precision and allows a better

interpretation of causal relationships than Granger causality. The application of transfer entropy in the field of macroeconomics includes the detection of the causal relationship between financial development and economic growth (Al khatib *et al.* 2023), energy consumption, foreign direct investment and economic growth (Akadiri & Ajmi 2020), and the causality of the financial services index between individual constituents (Zuhud *et al.* 2022). Akadiri and Ajmi (2020) are of the opinion that the method is also applicable in the case of missing values in the data series. The adaptability of transfer entropy to different data structures and types in the context of complex systems emphasises the potential of this method in addressing real-world problems to uncover more nuanced perceptions of their interrelationships and thus improve the accuracy and effectiveness of decision-making processes.

This study observed the quarterly time series data from the third quarter of 2011 to the second quarter of 2023 to ensure sufficient data points for estimating transfer entropy while capturing major economic disruptions that influenced national and OECD labour markets. This period encompasses the post-2008 Global Financial Crisis recovery phase and extends through the COVID-19 pandemic, both of which significantly impacted employment, unemployment, and economic growth across OECD economies. While most prior studies have examined labour market responses to economic fluctuations using annual data (Amor 2023; Eshun *et al.* 2023; Kesici 2022; Przekota *et al.* 2023), this study employs quarterly data, as seen in Meyer and Sanusi (2019) to provide a more granular understanding of dynamic causal interactions. The choice of quarterly frequency allows for a higher-resolution assessment of short-term causal relationships.

In summary, the literature to date demonstrates the complex interplay between the labour market and the economy in different geographical and temporal contexts. Nevertheless, most studies are variable-specific and examine either the dynamics between employment and GDP or the dimensions of unemployment and output. Various statistical methods have been employed to analyse these interactions, most of which are model-based parametric approaches. Transfer entropy has emerged as a distribution-free, non-parametric alternative to identify the complex interrelationships of real-world data. Although this method has been widely applied in industrial processes (Guo *et al.* 2015; Landman & Jämsä-Jounela 2016; Lindner *et al.* 2019; Zhang *et al.* 2022), neuroscience (Gao *et al.* 2019; Li & Li 2013; Ursino *et al.* 2020; Wibrat *et al.* 2014), and finances (Al khatib *et al.* 2023; Zuhud *et al.* 2022), to the best of our knowledge, its application in the labour market remains scarce. Thus, transfer entropy is deemed a powerful analytical tool to fill the gap in the literature by examining the intricate relationships between real GDP, employment, and unemployment in OECD member countries without prior assumptions about the distribution of data across countries. The ability of transfer entropy to capture inherent non-linear complexities between variables and remove biases in small samples can be used to gain a broader perspective on the dynamics and improve the policy framework for promoting sustainable economic growth.

3. Materials and Methods

3.1. Data source and description

This study leveraged secondary data published in the databases of international statistical organisations and the national statistical offices of selected OECD member countries. The value of real GDP at 2010 constant price (in millions of USD) was obtained from the Global Economic Monitor (World Bank 2023a), a regularly updated database which contains high-frequency country-level statistics on global economic events. In the meantime, the series on employment and unemployment levels were downloaded from the ILOSTAT, the database of the International Labour Organization (2023), which gathered annual, quarterly and monthly

labour statistics. In addition, employment data for selected countries were acquired from the OECD Employment and Labour Market Statistics (Organisation for Economic Co-operation and Development 2023a) to cater for missing values in the ILOSTAT series. The employment data for Lithuania and the United Kingdom were sourced from the Eurostat (2023) and Office for National Statistics United Kingdom (2023), respectively.

World Bank (2023b) defines real GDP as the sum of the gross value added by all producers within the country's borders, plus taxes levied, minus subsidies provided, all valued at constant prices. This reflects the production value, excluding the impact of inflation, and considers the depreciation of manufactured assets. A country's employment level is the sum of the population who produces goods and services to gain some form of compensation (International Labour Organization 2023; Organisation for Economic Co-operation and Development 2023b). Meanwhile, the level of unemployment within a country refers to the number of persons aged 15 and over who did not engage in paid employment or self-employment but were available for work and had taken specific steps in a specified recent period to seek paid employment or self-employment (International Labour Organization 2023).

As real GDP is a monetary value while employment and unemployment refer to the unit of persons, the annual growth rates of all three variables were calculated to fit into the transfer entropy model. The annual growth rate measures the percentage change of real GDP, employment and unemployment from one quarter to the same quarter in the preceding year. The growth rate can give direct insights into the performance of the variables and eliminate the issue of non-standard measures. After considering the availability of time series data for each country, this study used the annual growth of real GDP, annual growth of employment and annual growth of unemployment from the third quarter of 2011 to the second quarter of 2023.

3.2. Methodology

This study employed transfer entropy to explore the pairwise causal relationship between real GDP growth (GDP), employment growth (EMP) and unemployment growth (UNE) across 38 OECD member countries. Transfer entropy, introduced by Schreiber (2000), analyses the flow of information within complex systems. This model-free non-parametric method is highly adaptable to real-world labour and economic time series data since it can identify both linear and non-linear dependencies, in addition to accounting for temporal effects. Following the ability of transfer entropy to quantify the value of information flow between two or more systems, it is useful to draw causal inferences as well as to give insights into the strength of these relationships (Dimpfl & Peter 2013; Duan *et al.* 2013; Schreiber 2000). Further discussion on the calculation of transfer entropy is discussed in subsection 3.2.3 of this paper. Prior to the application of transfer entropy, the data were assessed for linear and non-linear associations and tested for the presence of unit roots. These preliminary analyses ensure the robustness of the subsequent transfer entropy analysis.

3.2.1 Linear and non-linear dependencies

In line with the recommendation from Schober *et al.* (2018), visual inspections of scatter plots were conducted to assess for linear associations between variables before we proceeded with the statistical tests using Pearson product-moment correlation. The correlation coefficient, r , measures the strength and direction of the linear relationship between a pair of variables (Puth *et al.* 2014; Schober *et al.* 2018). A positive linear trend can be established for $0 < r < 1$, where the pair moved in the same linear direction. Meanwhile, a negative linear trend is concluded for $-1 < r < 0$, with the pair displaying an opposite linear trend. The ability to determine a single linear relationship decreases as the absolute value of r declines (Puth *et al.* 2014). Eq. (1) presents the formula for calculating Pearson's correlation, r .

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} \quad (1)$$

where x_i and y_i denote the corresponding observations in variables X and Y up to n observations, while $\bar{x}$ and $\bar{y}$ are the respective means. The correlation coefficient is the ratio between the covariance of X and Y and the products of their standard deviations (Puth *et al.* 2014). The hypothesis assumed that the true population correlation coefficient, ρ , is not equal to zero, indicating the presence of a linear relationship between X and Y. The hypothesis was tested using a t-test with $n - 2$ degree of freedom, assuming that test statistic derived from the correlation coefficient follows a t-distribution. The calculation for the t-statistic is as in Eq. (2).

$$t = \frac{r}{\sqrt{\frac{1-r^2}{n-2}}} \quad (2)$$

The rejection region for this test, at a significance level of $\alpha = 0.05$, is given by Eq. (3), as follows:

$$|t| > t_{\alpha/2, n-2}, \quad (3)$$

where $t_{\alpha/2, n-2}$ is the critical value from the t-distribution table at $n - 2$ degrees of freedom. If the calculated test statistic falls within the rejection region, and the corresponding p-value is less than $\alpha = 0.05$, the null hypothesis is rejected, indicating a significant linear relationship between X and Y.

The non-linear dependency between a pair of variables was determined by calculating the distance correlation coefficient, $dCor(X, Y)$ (Edelmann *et al.* 2021; Martínez-Gómez *et al.* 2014; Székely *et al.* 2007). Equation (4) provides the calculation for $dCor(X, Y)$, where $dCov$ is the distance covariance, and $dVar$ is the distance variance.

$$dCor(X, Y) = \frac{dCov(X, Y)}{\sqrt{dVar(X, X)} \sqrt{dVar(Y, Y)}} \quad (4)$$

The alternative hypothesis assumed the existence of a dependency between a pair of variables while the null hypothesis stated independence. The observed $dCor(X, Y)$ was compared against a critical value derived from a permutation test at a significance level of $\alpha = 0.05$ to assess the statistical significance of the hypothesis. The null hypothesis of independence was rejected if the p-value was less than $\alpha = 0.05$, concluding the presence of a significant dependency between X and Y.

3.2.2. Stationarity of the time series

In order to measure transfer entropy, the time series must adhere to the requirement of stationarity (Behrendt *et al.* 2019; García-Medina & Hernandez 2020; Lindner *et al.* 2019). Analysing two or more non-stationary time series may lead to spurious causation. Non-stationary time series, often reflected by the presence of a unit root, imply that past values continue to influence future values, hindering their ability to revert to mean values. Therefore, the Augmented Dickey-Fuller (ADF) test was performed for the time series variables in all 38 OECD member countries to detect the presence of unit roots. Ordinary least square regression was applied to estimate the ADF statistics, as in Eq. (5).

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \dots + \beta_p y_{t-p} + \varepsilon_t \quad (5)$$

where Δy_t represents the first difference of y_t , β_0 to β_p are the estimated coefficients, p is the lag order, and ε_t is the error term. The alternative hypothesis assumed the absence of a unit root for a specific time series (stationary), while the null hypothesis claimed otherwise. The ADF test statistic was compared against the critical value at a significance level of $\alpha = 0.05$ to determine whether the null hypothesis could be rejected for a particular time series. The null hypothesis of non-stationarity was rejected if the test statistic was less than the critical value. For cases where the null hypothesis failed to be rejected, the non-stationary time series was differenced to remove the influence of trends and seasonality.

3.2.3. The application of transfer entropy

Transfer entropy to quantify the flow of information from the source variable (X) to the target variable (Y) is calculated as in Eq. (6).

$$TE_{X \rightarrow Y}(k, l) = \sum p(y_{t+1}, y_t^{(k)}, x_t^{(l)}) \log \frac{p(y_{t+1}|y_t^{(k)}, x_t^{(l)})}{p(y_{t+1}|y_t^{(k)})} \quad (6)$$

where,

$TE_{X \rightarrow Y}(k, l)$	transfer entropy from variable X with the history length of l for x_t to variable Y with the history length of k for y_t
$x_t^{(l)}$	the past history of X up to length l
$y_t^{(k)}$	the past history of Y up to length k
y_{t+1}	future value of Y
$p(y_{t+1}, y_t^{(k)}, x_t^{(l)})$	the joint probability distribution of the future value of Y, the past history of Y up to length k and the past history of X up to length l
$p(y_{t+1} y_t^{(k)}, x_t^{(l)})$	the conditional probability distribution of the future value of Y given the past value of Y up to length k and the past value of X up to length l
$p(y_{t+1} y_t^{(k)})$	the conditional probability distribution of the future value of Y given only the past value of Y up to length k
$\log \frac{p(y_{t+1} y_t^{(k)}, x_t^{(l)})}{p(y_{t+1} y_t^{(k)})}$	the logarithm of the ratio between the conditional probabilities to measure the difference between the conditional probability of Y's future value given both the past history of Y and X and the conditional probability of Y's future value given only the past history of Y

Transfer entropy can be interpreted as the predictive power gained about the future state of the target variable from the historical values of the source variable, beyond what is predicted by the target's past (Bossomaier *et al.* 2016; Schreiber 2000; Wibral *et al.* 2014). Relying on the assumption of the Markov process that the future state of a system depends on its immediate past, the calculation of transfer entropy leverages on the transition probabilities between consecutive states of the system (Bossomaier *et al.* 2016; Schreiber 2000). These probabilities are then conditioned on the past states of both the source and target variables (Schreiber 2000).

A non-zero transfer entropy value indicates an information flow from X to Y, which can be inferred as a causal link between the variables. Higher values imply a stronger influence of X on Y, while values nearing zero suggest a weak or negligible causal relationship. Since transfer entropy is a non-parametric method, Dimpfl and Peter (2013) proposed a way to calculate the standard error to establish the statistical significance of the transfer entropy values by bootstrapping the underlying Markov process. This method created simulated versions of process X as the relationship between X and Y is eliminated while keeping the behaviour of X intact. By repeatedly calculating transfer entropy on these simulated datasets, a distribution that might represent the results of the null hypothesis of no causal influence from X to Y is built. The observed transfer entropy is then compared against this null distribution to compute the standard error and the p-value. The null hypothesis is rejected if the p-value is less than the significance level ($\alpha = 0.05$), thereby concluding the presence of a causal relationship from X to Y.

Real-world data are often finite, owing to the limited number of observations or variations in the random samples. The analysis of transfer entropy on these data can lead to finite sample effects (Behrendt *et al.* 2019; Lungarella *et al.* 2007; Marschinski & Kantz 2002). Therefore, Marschinski and Kantz (2002) introduced the effective transfer entropy, which adjusts the transfer entropy after accounting for bias. In order to calculate the bias estimator, $TE_{X_{shuffled} \rightarrow Y}(k, l)$, a new source time series is created by randomly reshuffling the time series X, and in the process, removing any underlying associations within X and between X and Y. The average value of $TE_{X_{shuffled} \rightarrow Y}(k, l)$ diminishes towards zero with increased permutations, reflecting no information flow from shuffled X to Y. However, a non-zero $TE_{X_{shuffled} \rightarrow Y}(k, l)$ implies a small sample size. Consequently, effective transfer entropy is the difference between the value of transfer entropy in Eq. (6) and the bias estimator, calculated as in Eq. (7).

$$ETE_{X \rightarrow Y}(k, l) = TE_{X \rightarrow Y}(k, l) - TE_{X_{shuffled} \rightarrow Y}(k, l) \quad (7)$$

Overall, adopting transfer entropy enhances the framework for investigating causal relationships among variables. This approach allows for identifying directional influences and their intensities and uncovers the intricate interplay between real GDP, employment, and unemployment. Furthermore, transfer entropy effectively reduces biases associated with limited samples, thereby improving the trustworthiness of conclusions.

4. Results and Discussions

4.1. Preliminary findings

This section explores the initial insights into the linear and non-linear dependencies between real GDP growth, employment growth and unemployment growth for the 38 OECD member countries, as well as the stationarity of the data. Table 1 presents the Pearson correlation coefficients, offering a preliminary understanding of the relationships among these variables. Strong evidence at a 95 per cent significance level supports a positive correlation between real GDP and unemployment in 31 countries, reflecting the linear association of the pair of variables. Twelve countries exhibit strong linear relationships with coefficients greater than 0.7, namely Australia, Austria, Canada, Chile, Costa Rica, Denmark, Greece, Iceland, Mexico, Norway, Spain and the United States. However, the null hypothesis of no relationship could not be rejected for seven countries – Estonia, Israel, Latvia, Lithuania, Luxembourg, New Zealand and Türkiye – indicating a lack of linear coherence between GDP and employment growth trends in these countries. This suggests that employment trends may be influenced by economic

or policy factors differently than the broader OECD context. These aspects are further examined in the following discussion on structural labour market characteristics and macroeconomic factors.

Table 1: Pearson product-moment correlation linearity analysis

Country	GDP and EMP		GDP and UNE		EMP and UNE	
	p-value	Correlation coefficient	p-value	Correlation coefficient	p-value	Correlation coefficient
Australia	0.0000	0.7058	0.0000	-0.6526	0.0000	-0.8004
Austria	0.0000	0.7621	0.0262	-0.3207	0.0000	-0.6099
Belgium	0.0002	0.5192	0.6285	0.0716	0.0001	-0.5240
Canada	0.0000	0.9389	0.0000	-0.9022	0.0000	-0.9118
Chile	0.0000	0.8320	0.0000	-0.8267	0.0000	-0.8925
Colombia	0.0000	0.6655	0.0000	-0.8127	0.0000	-0.7707
Costa Rica	0.0000	0.7293	0.0000	-0.6844	0.0302	-0.3131
Czech Republic	0.0001	0.5357	0.0000	-0.6485	0.0000	-0.6654
Denmark	0.0000	0.7126	0.0001	-0.5223	0.0003	-0.5001
Estonia	0.6124	0.0750	0.0095	-0.3709	0.0000	-0.5718
Finland	0.0000	0.6762	0.0005	-0.4851	0.0000	-0.6004
France	0.0000	0.6214	0.0045	0.4030	0.8783	-0.0227
Germany	0.0047	0.4017	0.0000	-0.6625	0.0000	-0.7377
Greece	0.0000	0.7384	0.0000	-0.5816	0.0000	-0.8836
Hungary	0.0000	0.6073	0.0000	-0.6657	0.0000	-0.7545
Iceland	0.0000	0.7544	0.0000	-0.6154	0.0000	-0.7939
Ireland	0.0067	0.3863	0.8463	0.0287	0.0001	-0.5505
Israel	0.1104	0.2334	0.2080	-0.1850	0.9668	0.0062
Italy	0.0008	0.4683	0.9084	0.0171	0.0011	-0.4556
Japan	0.0112	0.3632	0.0136	-0.3540	0.0001	-0.5468
Republic of Korea	0.0000	0.6310	0.2387	-0.1734	0.0075	-0.3813
Latvia	0.4707	0.1066	0.0001	-0.5465	0.0548	-0.2791
Lithuania	0.6902	0.0590	0.0000	-0.5581	0.0000	-0.5778
Luxembourg	0.0725	0.2616	0.0382	-0.3002	0.1110	-0.2330
Mexico	0.0000	0.9164	0.0026	-0.4248	0.0141	-0.3521
Netherlands	0.0000	0.6425	0.0009	-0.4648	0.0000	-0.5876
New Zealand	0.9209	0.0147	0.6388	0.0695	0.0699	-0.2639
Norway	0.0000	0.7128	0.0002	-0.5142	0.0000	-0.6028
Poland	0.0000	0.5776	0.0138	-0.3534	0.0001	-0.5422
Portugal	0.0000	0.6548	0.0471	-0.2881	0.0000	-0.7507
Slovak Republic	0.0000	0.5675	0.0013	-0.4499	0.0000	-0.6648
Slovenia	0.0143	0.3515	0.0000	-0.6643	0.0000	-0.6634
Spain	0.0000	0.7525	0.0000	-0.5721	0.0000	-0.8773
Sweden	0.0000	0.5778	0.0004	-0.4877	0.0000	-0.8148
Switzerland	0.0025	0.4263	0.1304	-0.2214	0.0001	-0.5210
Türkiye	0.2851	0.1575	0.0394	-0.2984	0.1692	-0.2017
United Kingdom	0.0044	0.4045	0.0019	-0.4376	0.0000	-0.8494
USA	0.0000	0.8759	0.0000	-0.8083	0.0000	-0.9427

Note: GDP represents the annual percentage change of real GDP at the 2010 constant price; EMP represents the annual percentage change of employment; UNE represents the annual percentage change of unemployment. The null hypothesis assumes no linear relationship between the pair of variables. It is rejected for a p-value less than $\alpha = 0.05$ significance level .

Linear relationships between real GDP growth and unemployment growth are confirmed for 31 countries, with 30 countries showing the expected inverse relationship that aligns with Okun (1962). Notably strong inverse relationships are observed in Canada, Chile, Colombia and the United States. Nevertheless, the correlation coefficient reported for France is greater than 0, suggesting that positive real GDP growth could elevate the unemployment situation in the country while negative growth could ease unemployment. This hints that structural changes or other macroeconomic factors must be taken together when evaluating the unemployment situation in the country.

The linear relationship between employment growth and unemployment growth across 32 of OECD countries indicates inverse correlations, parallel to the general dynamics in the labour market. In particular, 13 countries exhibit strong negative correlations, with Canada and the United States recording coefficients close to -0.9. On the other hand, six countries, namely France, Israel, Latvia, Luxembourg, New Zealand and Türkiye, did not exhibit a significant linear relationship between these variables, potentially due to the labour market's inherent structural issues and policy frameworks that shape employment patterns and labour mobility.

Distance correlation analysis was conducted to further examine potential non-linear associations (Table 2). Although the values of distance correlation coefficients predominantly support the earlier results of Pearson's correlation, this method manages to identify additional dependencies in several countries, thereby reinforcing the need for a more flexible, non-parametric approach to capture complex dynamics. Notably, Israel and Türkiye show dependencies between real GDP growth and employment, while Belgium, Ireland, Israel and Italy reveal dependencies between real GDP and unemployment. France, Israel and Türkiye also display dependencies between employment and unemployment, further suggesting heterogenous labour market structures across OECD countries. Interestingly, New Zealand is the only country without any pairwise association between all three pairs of variables, either linear or non-linear.

Although these findings offer initial ideas of the dependencies between the variables, correlation analyses cannot establish causality. Hence, an advanced and robust method like transfer entropy is employed to gauge a more comprehensive knowledge of the complex relationship between the labour market and the economy.

Table 2: Distance Correlation Dependency Analysis

Country	GDP and EMP		GDP and UNE		EMP and UNE	
	p-value	Distance coefficient	p-value	Distance coefficient	p-value	Distance coefficient
Australia	0.0010	0.6168	0.0010	0.6430	0.0010	0.7868
Austria	0.0010	0.7694	0.0010	0.5990	0.0010	0.5609
Belgium	0.0010	0.5757	0.0030	0.4346	0.0010	0.4904
Canada	0.0010	0.8312	0.0010	0.8709	0.0010	0.9192
Chile	0.0010	0.7695	0.0010	0.8115	0.0010	0.8420
Colombia	0.0010	0.6186	0.0010	0.7893	0.0010	0.7496
Costa Rica	0.0010	0.6428	0.0010	0.6742	0.0210	0.3866
Czech Republic	0.0010	0.5720	0.0010	0.7825	0.0010	0.6707
Denmark	0.0010	0.7222	0.0010	0.5270	0.0010	0.4673
Estonia	0.2228	0.2940	0.0090	0.4255	0.0010	0.5512
Finland	0.0010	0.5969	0.0010	0.5747	0.0010	0.7507
France	0.0010	0.5925	0.0010	0.4903	0.0290	0.3617
Germany	0.0010	0.5941	0.0010	0.7342	0.0010	0.7139
Greece	0.0010	0.7918	0.0010	0.7108	0.0010	0.9185
Hungary	0.0010	0.5982	0.0010	0.7669	0.0010	0.7479
Iceland	0.0010	0.7072	0.0010	0.6032	0.0010	0.7292

Table 2 (Continued)

Ireland	0.0060	0.4479	0.0100	0.4061	0.0010	0.6627
Israel	0.0160	0.4197	0.0030	0.4398	0.0010	0.5060
Italy	0.0010	0.6682	0.0010	0.5439	0.0010	0.6270
Japan	0.0090	0.4236	0.0030	0.5077	0.0010	0.5494
Republic of Korea	0.0010	0.5941	0.5265	0.2556	0.0050	0.4348
Latvia	0.3157	0.2752	0.0010	0.5963	0.1678	0.3019
Lithuania	0.3716	0.2730	0.0010	0.5556	0.0020	0.5605
Luxembourg	0.3427	0.2631	0.0210	0.3857	0.1708	0.2901
Mexico	0.0010	0.8086	0.0010	0.6700	0.0010	0.5261
Netherlands	0.0010	0.6935	0.0010	0.6997	0.0010	0.6460
New Zealand	0.7363	0.2413	0.1489	0.3509	0.0849	0.3333
Norway	0.0010	0.6995	0.0010	0.5105	0.0010	0.5730
Poland	0.0010	0.5931	0.0010	0.5595	0.0010	0.5904
Portugal	0.0010	0.8342	0.0010	0.6106	0.0010	0.7381
Slovak Republic	0.0010	0.6383	0.0010	0.6017	0.0010	0.6602
Slovenia	0.0010	0.5320	0.0010	0.7175	0.0010	0.6749
Spain	0.0010	0.8800	0.0010	0.8138	0.0010	0.8935
Sweden	0.0010	0.5715	0.0010	0.5503	0.0010	0.7801
Switzerland	0.0010	0.4989	0.1019	0.3458	0.0020	0.4865
Türkiye	0.0090	0.4244	0.0070	0.4061	0.0160	0.3891
United Kingdom	0.0010	0.7052	0.0010	0.7148	0.0010	0.8133
USA	0.0010	0.8151	0.0010	0.8193	0.0010	0.9621

Note: GDP represents the annual percentage change of real GDP at the 2010 constant price; EMP represents the annual percentage change of employment; UNE represents the annual percentage change of unemployment. The null hypothesis assumes no linear relationship between the pair of variables. It is rejected for a p-value less than $\alpha = 0.05$ significance level.

Table 3 presents the results of the ADF unit root test, providing insights into the stationarity of the time series across OECD countries, which is the prerequisite of transfer entropy analysis. The time series data of real GDP growth in 36 OECD member countries exhibit integration at level, whereas the data for Iceland and Ireland demonstrate first-order integration. The time series for employment growth are integrated at level for 23 member countries, at second order for 14 countries, and at the third order for the Czech Republic. The unemployment growth time series for 23 member countries are integrated at level, another 14 integrated at the first order, while the unemployment growth in the Slovak Republic is integrated at the second order. In summary, different time series variables in each country achieve stationarity at varying orders of integration. Considering this, the transfer entropy analysis for 15 countries is based on stationary time series at level, comprising 48 data points. In addition, the analysis of pairwise causality in 21 OECD member countries utilises the time series integrated at the first order with 47 observations. Meanwhile, 46 data series points are analysed for the Czech Republic and the Slovak Republic, respectively, since selected variables for these countries are integrated at the second order.

Table 3: ADF Unit Root Test

Country	Real GDP growth	Employment growth	Unemployment growth	Time series analysis
	Integrated at	Integrated at	Integrated at	Integrated at
Australia	I(0)	I(1)	I(0)	I(1)
Austria	I(0)	I(0)	I(0)	I(0)
Belgium	I(0)	I(0)	I(1)	I(1)
Canada	I(0)	I(0)	I(0)	I(0)
Chile	I(0)	I(0)	I(0)	I(0)

Table 3 (Continued)

Colombia	I(0)	I(0)	I(1)	I(1)
Costa Rica	I(0)	I(0)	I(1)	I(1)
Czech Republic	I(0)	I(2)	I(1)	I(2)
Denmark	I(0)	I(1)	I(0)	I(1)
Estonia	I(0)	I(0)	I(0)	I(0)
Finland	I(0)	I(0)	I(0)	I(0)
France	I(0)	I(0)	I(0)	I(0)
Germany	I(0)	I(0)	I(0)	I(0)
Greece	I(0)	I(0)	I(0)	I(0)
Hungary	I(0)	I(0)	I(0)	I(0)
Iceland	I(1)	I(1)	I(1)	I(1)
Ireland	I(1)	I(0)	I(0)	I(1)
Israel	I(0)	I(1)	I(0)	I(1)
Italy	I(0)	I(0)	I(0)	I(0)
Japan	I(0)	I(1)	I(1)	I(1)
Republic of Korea	I(0)	I(0)	I(1)	I(1)
Latvia	I(0)	I(0)	I(0)	I(0)
Lithuania	I(0)	I(1)	I(1)	I(1)
Luxembourg	I(0)	I(0)	I(0)	I(0)
Mexico	I(0)	I(0)	I(1)	I(1)
Netherlands	I(0)	I(1)	I(1)	I(1)
New Zealand	I(0)	I(1)	I(0)	I(1)
Norway	I(0)	I(0)	I(0)	I(0)
Poland	I(0)	I(1)	I(1)	I(1)
Portugal	I(0)	I(0)	I(1)	I(1)
Slovak Republic	I(0)	I(1)	I(2)	I(2)
Slovenia	I(0)	I(1)	I(1)	I(1)
Spain	I(0)	I(0)	I(1)	I(1)
Sweden	I(0)	I(1)	I(0)	I(1)
Switzerland	I(0)	I(1)	I(0)	I(1)
Türkiye	I(0)	I(1)	I(0)	I(1)
United Kingdom	I(0)	I(0)	I(0)	I(0)
USA	I(0)	I(0)	I(0)	I(0)

Note: I(0) means that the time series is integrated at level, I(1) integrated at the first order and I(2) integrated at second order. The null hypothesis assumed that the time series has a unit root (non-stationary). This hypothesis is rejected for p-value less than $\alpha = 0.05$ significance level.

4.2. Results and discussion on causality between labour and economy

The empirical results of the transfer entropy analysis for the three pairs of variables in 38 OECD member countries are presented in Tables 4 to 6, respectively. These findings provide empirical insights into the influences of labour market and economic performance on each other across OECD countries, highlighting the diverse and structural factors shaping these interactions.

Transfer entropy analysis identifies statistically significant causality between real GDP growth and employment growth in 16 countries (Table 4). Significant values of transfer entropy support the evidence of unidirectional causality from real GDP growth towards employment growth in the Republic of Korea and Austria, aligning with previous studies (Colacchio & Vergori 2022; Kesici 2022). In the Republic of Korea, employment opportunities are sustained by a high-tech, export-oriented economy (Organisation for Economic Co-operation and Development 2024b), where automation adoption and industrial innovation strategies bolster the demand for skilled employment. Similarly, Austria's employment dynamics are highly responsive to GDP change, as economic expansion stimulates labour demand through increased

domestic consumption, fiscal incentives, and industrial activity. Additionally, labour market reforms, including tax incentives and policies promoting female and older workforce participation, have enhanced employment resilience. Austria's economic reliance on Germany's external demand further amplifies the responsiveness of job creation to cross-border economic conditions (Organisation for Economic Co-operation and Development 2024b). These findings underscore the pivotal role of economic expansions in creating job opportunities within these countries.

On the other hand, the reverse causality from employment growth to real GDP growth is detected in ten countries, with Australia, Denmark, and the Netherlands exhibiting the highest effective transfer entropy values, followed by Iceland, Lithuania, Sweden, Slovenia, Switzerland, Türkiye, and Germany. In Australia, strong employment-led economic growth is attributed to labour market flexibility, skilled immigration policy, and a commitment towards enhancing workforce capabilities through the formulation of the Skills Priority List (Organisation for Economic Co-operation and Development 2024b). A similar trend is evident in Denmark, where training and upskilling in science and technology, and tax reform have increased labour productivity and subsequently boosted GDP growth (Organisation for Economic Co-operation and Development 2024b). Likewise, the impact of Netherlands' employment over real GDP is supported by key policy directions which integrate labour market reforms, taxation policies, digitalisation, and targeted investments in labour force participation (Organisation for Economic Co-operation and Development 2024b).

Table 4: Transfer Entropy between Real GDP Growth and Employment Growth

Country	Causal relationship from GDP to EMP			Causal relationship from EMP to GDP		
	Transfer entropy	Effective transfer entropy	p-value	Transfer entropy	Effective transfer entropy	p-value
Australia	0.0072	0.0000	0.6700	0.3988	0.3645*	0.0000
Austria	0.1473	0.1197*	0.0200	0.1055	0.0777	0.1000
Belgium	0.1669	0.1428*	0.0133	0.1096	0.0824*	0.0267
Canada	0.0000	0.0000	0.9700	0.0000	0.0000	0.9733
Chile	0.0000	0.0000	0.8600	0.0000	0.0000	0.8933
Colombia	0.0031	0.0000	0.6400	0.0031	0.0000	0.6967
Costa Rica	0.1047	0.0710	0.1133	0.0450	0.0099	0.2233
Czech Republic	0.1095	0.0742	0.0567	0.0076	0.0000	0.4967
Denmark	0.0129	0.0000	0.5567	0.2095	0.1789*	0.0000
Estonia	0.0638	0.0369	0.1267	0.1063	0.0772	0.0533
Finland	0.0471	0.0179	0.2900	0.0061	0.0000	0.8400
France	0.1473	0.1137*	0.0200	0.1473	0.1177*	0.0200
Germany	0.1063	0.0760	0.0567	0.1489	0.1198*	0.0067
Greece	0.0061	0.0000	0.5933	0.0093	0.0000	0.4867
Hungary	0.1079	0.0743	0.0567	0.0495	0.0196	0.1867
Iceland	0.0881	0.0570	0.1100	0.1899	0.1602*	0.0000
Ireland	0.0048	0.0000	0.6000	0.0098	0.0000	0.6833
Israel	0.0098	0.0000	0.5967	0.1080	0.0763	0.0800
Italy	0.2065	0.1707*	0.0067	0.1489	0.1198*	0.0267
Japan	0.0098	0.0000	0.4567	0.1096	0.0757	0.0700
Republic of Korea	0.2095	0.1742*	0.0100	0.0507	0.0198	0.2067
Latvia	0.1079	0.0833	0.0500	0.0653	0.0280	0.1667
Lithuania	0.0098	0.0000	0.4267	0.1683	0.1443*	0.0067
Luxembourg	0.0678	0.0387	0.1167	0.0678	0.0370	0.1133
Mexico	0.0450	0.0120	0.2400	0.0024	0.0000	0.9667
Netherlands	0.0129	0.0000	0.5700	0.2095	0.1756*	0.0033

Table 4 (Continued)

New Zealand	0.0098	0.0000	0.6433	0.0507	0.0233	0.1867
Norway	0.1032	0.0682	0.1200	0.0440	0.0129	0.2067
Poland	0.1250	0.0884*	0.0233	0.1250	0.0960*	0.0333
Portugal	0.0072	0.0000	0.6233	0.0098	0.0000	0.6467
Slovak Republic	0.0103	0.0000	0.6300	0.1097	0.0738	0.0533
Slovenia	0.0072	0.0000	0.6033	0.1669	0.1380*	0.0167
Spain	0.0072	0.0000	0.6867	0.1096	0.0752	0.0567
Sweden	0.0098	0.0000	0.5967	0.1669	0.1428*	0.0233
Switzerland	0.0687	0.0444	0.1667	0.1669	0.1360*	0.0033
Türkiye	0.0098	0.0000	0.5100	0.1669	0.1371*	0.0133
United Kingdom	0.1055	0.0682	0.0600	0.0653	0.0333	0.1767
USA	0.1032	0.0700	0.1100	0.0022	0.0000	0.9633

Note: GDP represents the annual percentage change of real GDP at the 2010 constant price, while EMP represents the annual percentage change of employment. The null hypothesis that assumed no causal relationship from the source variable to the target variable is rejected for a p-value less than $\alpha = 0.05$ significance level. * denotes the value of effective transfer entropy with corresponding statistical significant value of transfer entropy.

The analysis further reveals bidirectional causality between real GDP growth and employment growth in Belgium, France, Italy, and Poland, which is consistent with earlier studies by He (2018) and Meyer and Sanusi (2019). These interdependencies reflect a cyclical feedback loop, where economic performance and employment conditions continuously influence each other. However, the nature of this relationship varies across countries, highlighting structural differences in the responsiveness of the labour market and policy frameworks. In Italy and Belgium, the stronger influence of real GDP growth on employment growth emphasises the key role of economic expansion in advancing employment, particularly in high-tech manufacturing and knowledge-intensive services sectors (European Union 2024; Organisation for Economic Co-operation and Development 2024a; 2024b). In contrast, employment-led economic growth is more prominent in France and Poland, where labour market reforms and workforce training initiatives contribute to economic expansion (Organisation for Economic Co-operation and Development 2024a; 2024b). In the meantime, the exertion of fiscal constraints and labour market reform strategies in Belgium address the challenges of fiscal deficit and labour shortages respectively, thereby reinforcing the influence of GDP and employment on each other (Organisation for Economic Co-operation and Development 2024b). These reciprocal relationships between real GDP and employment emphasise the need for a holistic policy framework that integrates strategies to foster employment and the economy. In the meantime, the lack of causal relationships between real GDP and employment in twelve OECD countries indicates the heterogeneity in the labour market and economic dynamics across these countries, especially due to country-specific factors such as institutional frameworks, economic policies or structural issues.

Table 5 reports the results of the transfer entropy between real GDP growth and unemployment growth. Statistically significant causal relationships are detected in 20 OECD countries. Eight countries display unidirectional causal relationships from real GDP growth to unemployment growth, namely New Zealand, Australia, Luxembourg, Austria, Chile, Spain, , Estonia, and Finland. This aligns with previous findings (Altunöz 2024; Boga 2020; Sahoo & Sahoo 2019) that economic growth reduces unemployment by expanding production and creating jobs. High effective transfer entropy values from real GDP to unemployment are observed in New Zealand and Australia, reflecting the function of economic growth in absorbing labour market slack. New Zealand's economic expansion in labour-intensive industries reduced unemployment, particularly among medium and low-skilled labour. However, low productivity growth and high capital costs continue to pose structural challenges

that hinder investment in high-skilled employment, ultimately affecting long-term economic prospects (Organisation for Economic Co-operation and Development 2024b). Australia's economic expansion, anchored by fiscal stimulus and easing of monetary policy, has reduced unemployment by filling in job demand in critical sectors such as construction and services (Organisation for Economic Co-operation and Development 2024b).

Table 5: Transfer Entropy between Real GDP Growth and Unemployment Growth

Country	Causal relationship from GDP to UNE			Causal relationship from UNE to GDP		
	Transfer entropy	Effective transfer entropy	p-value	Transfer entropy	Effective transfer entropy	p-value
Australia	0.2957	0.2512	0.0000	0.0507	0.0223	0.2167
Austria	0.1891	0.1528	0.0167	0.1055	0.0693	0.1067
Belgium	0.0000	0.0000	0.9933	0.0000	0.0000	0.9833
Canada	0.0000	0.0000	0.9533	0.0000	0.0000	0.9433
Chile	0.1883	0.1481	0.0100	0.0440	0.0169*	0.2133
Colombia	0.1096	0.0719	0.0667	0.2087	0.1726	0.0067
Costa Rica	0.0098	0.0000	0.4800	0.1071	0.0714	0.0800
Czech Republic	0.1079	0.0785	0.0500	0.2126	0.1833*	0.0033
Denmark	0.1498	0.1156*	0.0367	0.1498	0.1217*	0.0333
Estonia	0.1079	0.0736*	0.0367	0.0093	0.0000	0.4133
Finland	0.1079	0.0780*	0.0300	0.0126	0.0000	0.4967
France	0.0022	0.0000	0.9600	0.0022	0.0000	0.9733
Germany	0.1032	0.0797	0.0933	0.0022	0.0000	0.9767
Greece	0.0069	0.0000	0.5933	0.0069	0.0000	0.6467
Hungary	0.0046	0.0000	0.8167	0.0046	0.0000	0.8100
Iceland	0.0440	0.0077	0.1800	0.0022	0.0000	0.9633
Ireland	0.0482	0.0091	0.2467	0.1096	0.0850	0.0667
Israel	0.0098	0.0000	0.5100	0.0661	0.0317	0.1667
Italy	0.0030	0.0000	0.6967	0.0046	0.0000	0.8267
Japan	0.1498	0.1229*	0.0467	0.1933	0.1589*	0.0067
Republic of Korea	0.1096	0.0761*	0.0267	0.1080	0.0755*	0.0467
Latvia	0.0030	0.0000	0.6233	0.0046	0.0000	0.8067
Lithuania	0.0072	0.0000	0.4833	0.3577	0.3304*	0.0000
Luxembourg	0.1914	0.1600*	0.0000	0.1079	0.0856	0.0633
Mexico	0.0482	0.0147	0.2167	0.1498	0.1141	0.0500
Netherlands	0.1063	0.0723*	0.0467	0.2095	0.1760*	0.0033
New Zealand	0.2957	0.2536*	0.0000	0.0072	0.0000	0.5867
Norway	0.0093	0.0000	0.5500	0.1055	0.0668*	0.0333
Poland	0.1071	0.0701	0.0800	0.1071	0.0762	0.0767
Portugal	0.1055	0.0906*	0.0233	0.2087	0.1762*	0.0067
Slovak Republic	0.0519	0.0187	0.1867	0.0050	0.0000	0.6167
Slovenia	0.0687	0.0421	0.1167	0.1250	0.0923*	0.0300
Spain	0.1498	0.1188*	0.0167	0.0064	0.0000	0.8100
Sweden	0.1080	0.0748	0.0667	0.0098	0.0000	0.6500
Switzerland	0.0482	0.0093	0.1933	0.1514	0.1213*	0.0133
Türkiye	0.1063	0.0725	0.0733	0.0072	0.0000	0.5867
United Kingdom	0.2316	0.1963*	0.0033	0.1473	0.1191*	0.0467
USA	0.0440	0.0049	0.1900	0.1032	0.0666	0.0900

Note: GDP represents the annual percentage change of real GDP at the 2010 constant price, while UNE represents the annual percentage change of unemployment. The null hypothesis that assumed no causal relationship from the source variable to the target variable is rejected for a p-value less than $\alpha = 0.05$ significance level. * denotes the value of effective transfer entropy with corresponding statistical significant value of transfer entropy.

Meanwhile, reverse causality from unemployment to real GDP is found in Lithuania, the Czech Republic, Colombia, Switzerland, Slovenia, and Norway. This corroborates the findings of an earlier study by Shiferaw (2023) and shows that any shock in the unemployment situation can affect the economic growth trajectory, reflecting the importance of active labour market policy towards fostering growth. In Lithuania and Czech Republic, where high value of effective transfer entropy are observed, declining unemployment supports GDP growth through stronger household consumption, productivity improvements, and rising labour force participation (Organisation for Economic Co-operation and Development 2024b). Reducing unemployment in Norway, Slovenia, and Switzerland contributes to economic growth by addressing mismatches between labour demand and supply. While these countries face labour shortages in high-skilled sectors such as technology and healthcare, unemployment remains elevated among low-skilled and older workers. Governments have introduced targeted job training, vocational education reforms, and pension adjustments to enhance workforce participation and ensure a more balanced labour market. These policies help sustain economic growth despite demographic challenges and evolving labour market demands by reskilling unemployed individuals and improving incentives for labour force retention (Organisation for Economic Co-operation and Development 2024b).

In line with Özen (2022), mutual causality between economic growth and unemployment is detected for Denmark, Japan, the Republic of Korea, the Netherlands, Portugal and the United Kingdom. A more pronounced impact from real GDP to unemployment is exhibited in the Republic of Korea and the United Kingdom. Meanwhile, unemployment exerts a stronger influence on GDP in Denmark, Japan, the Netherlands, and Portugal. These findings emphasise the importance of integrated economic and labour market policies. Causality between real GDP and unemployment failed to be established in the remaining 18 countries, indicating diverse economic fundamentals or labour market structures across these OECD countries.

The study also explores the interaction between employment and unemployment, revealing the dynamics within the labour market (Table 6). The causal relationship between the pair of variables is confirmed in twelve OECD countries. Unidirectional causality from employment growth to unemployment growth is uncovered in six countries, namely Finland, Iceland, Chile, Ireland, the Republic of Korea and Sweden. This suggests that the increase in labour demand can reduce unemployment following the absorption into the workforce. On the contrary, the reverse causality from unemployment growth to employment growth is identified for Mexico, the United Kingdom, Belgium, Slovenia, France, and Poland. This could indicate underlying structural issues in the labour market, such as skill shortages and mismatch, wage rigidity, and technological changes.

The interplay between real GDP, employment, and unemployment reflects the underlying mechanisms driving economic growth and labour market outcomes across OECD countries. Economic expansion, as shown by rising GDP over time, is a sign of a healthy economy. This, in turn, can boost the confidence of consumers and investors, subsequently motivating demand for goods and services. In response, firms tend to expand production and hire more workers to meet these demands, leading to employment gain and a simultaneous reduction in unemployment. Strategic investments can further accelerate output growth, attributing to the firm expanding operations and hiring new talent. Capital investments in machinery equipment and infrastructure can strengthen and propel economic growth, especially in labour-intensive sectors, further stimulating the expansion of the labour market by increasing employment and reducing unemployment. In addition, investments in technology and research can open up the opportunity to create skilled jobs. Although this may not cause the desired proportional decline in unemployment, the role of technology in enhancing productivity will propel the economy. Thus, the dynamics between GDP and the labour market are also characterised by types of investment and the focus on specific industries.

Table 6: Transfer Entropy between Employment Growth and Unemployment Growth

Country	Causal relationship from EMP to UNE			Causal relationship from UNE to EMP		
	Transfer entropy	Effective transfer entropy	p-value	Transfer entropy	Effective transfer entropy	p-value
Australia	0.1071	0.0612	0.0567	0.0661	0.0290	0.1967
Austria	0.0440	0.0002	0.1967	0.0022	0.0000	0.9633
Belgium	0.1096	0.0799	0.0600	0.1669	0.1320*	0.0100
Canada	0.0000	0.0000	0.9667	0.0000	0.0000	0.9633
Chile	0.1883	0.1573*	0.0067	0.0440	0.0088	0.1800
Colombia	0.1096	0.0740	0.0967	0.1071	0.0708	0.0733
Costa Rica	0.0098	0.0000	0.5500	0.0098	0.0000	0.4633
Czech Republic	0.0050	0.0000	0.5000	0.1095	0.0821	0.0633
Denmark	0.0048	0.0000	0.6200	0.0095	0.0000	0.6600
Estonia	0.0495	0.0181	0.1833	0.1063	0.0786	0.1000
Finland	0.2491	0.2194*	0.0000	0.0495	0.0147	0.2533
France	0.0471	0.0181	0.2200	0.1473	0.1163*	0.0300
Germany	0.0495	0.0146	0.2000	0.1063	0.0714	0.1067
Greece	0.0069	0.0000	0.6633	0.0471	0.0130	0.1667
Hungary	0.0471	0.0156	0.2367	0.1055	0.0706	0.0900
Iceland	0.1883	0.1593*	0.0167	0.0440	0.0018	0.1800
Ireland	0.1933	0.1527*	0.0000	0.0482	0.0233	0.1633
Israel	0.0072	0.0000	0.5933	0.1096	0.0775	0.0733
Italy	0.0471	0.0100	0.1700	0.1063	0.0804	0.0900
Japan	0.0507	0.0178	0.2033	0.0072	0.0000	0.6067
Republic of Korea	0.1685	0.1407*	0.0067	0.0661	0.0396	0.1733
Latvia	0.0061	0.0000	0.4633	0.1079	0.0716	0.0500
Lithuania	0.0482	0.0212	0.2567	0.1071	0.0769	0.0867
Luxembourg	0.0495	0.0186	0.2267	0.0653	0.0354	0.2267
Mexico	0.0482	0.0137	0.2533	0.2360	0.1936*	0.0033
Netherlands	0.0885	0.0612	0.0633	0.1078	0.0694	0.0767
New Zealand	0.1071	0.0668	0.0733	0.0132	0.0000	0.5367
Norway	0.0495	0.0158	0.2400	0.0069	0.0000	0.6667
Poland	0.0661	0.0360	0.1733	0.1096	0.0808*	0.0467
Portugal	0.0064	0.0000	0.4000	0.0098	0.0000	0.4833
Slovak Republic	0.0676	0.0355	0.1400	0.0103	0.0000	0.4733
Slovenia	0.1071	0.0730	0.0667	0.1498	0.1190*	0.0100
Spain	0.0507	0.0240	0.2433	0.0072	0.0000	0.6433
Sweden	0.1669	0.1342*	0.0100	0.0132	0.0000	0.4833
Switzerland	0.0482	0.0193	0.1800	0.1096	0.0790	0.0600
Türkiye	0.0064	0.0000	0.4433	0.0098	0.0000	0.5367
United Kingdom	0.0471	0.0111	0.2400	0.1899	0.1589*	0.0133
USA	0.0440	0.0057	0.2400	0.0022	0.0000	0.9600

Note: EMP represents the annual percentage change of employment, while UNE represents the annual percentage change of unemployment. The null hypothesis that assumed no causal relationship from the source variable to the target variable is rejected for a p-value less than $\alpha = 0.05$ significance level.

* denotes the value of effective transfer entropy with corresponding statistical significant value of transfer entropy.

From another perspective, expanding the labour market directly contributes to the increase in real GDP. The surge in employment increases disposable income, which in turn, stimulates demand from firms and the subsequent rise in output. This cycle facilitates productivity and further economic growth. Firms may also realign focus towards human capital investment by training and upskilling their workforce to foster innovation and value creation, thereby

enhancing long-term economic growth. On the flip side, the rise in unemployment in an economy affects purchasing power due to diminishing disposable income. In addition, it can also cause a negative perception by potential investors. This can cause a lower revenue and the successive slowdown or decline of real GDP. The shift of labour force in an economy to unemployment can also hinder productivity, compromise output and cause a drop in real GDP.

Despite a clear inverse relationship between employment and unemployment, there are instances where a decrease in unemployment does not cause a rise in overall employment within a country. This phenomenon can be ascribed to government interventions in the form of active labour market policies aimed at upholding jobs and mitigating unemployment, specifically during economic contractions. For example, governments may offer wage subsidies to businesses in the event of dwindling output to retain employees during difficult situations. Furthermore, the drop in unemployment may also stem from individuals exiting the labour force due to limited employment prospects in the market.

The interdependencies between real GDP, employment and unemployment in a feedback loop means that the change in one can reinforce the change in the other in a cycle. However, the effects of these changes on each other may not be immediate due to technological advances and policy interventions. Productivity gained from investment in technology may accelerate the growth of real GDP without the proportional increase in employment and the corresponding decrease in unemployment. In the meantime, fiscal policy interventions may substantially influence the labour market and the economy. An upsurge in government expenditure, such as through investments in infrastructure projects and injection of stimulus, can lead to employment creation and simultaneously ease unemployment. In contrast, imposing higher taxes on businesses and individuals could reduce disposable income and demand, consequently affecting the labour market. The revision of monetary policy by central banks through adjustments in interest rates can also impact the labour market and output. Reducing the interest rates opens up investment opportunities, encourages demand and promotes borrowing, thereby potentially enabling job creation and accelerating GDP growth.

While the findings of this study provide valuable insights into the interactions between real GDP, employment, and unemployment, the external validity may be limited to the context of OECD member countries. OECD countries often feature relatively structured labour markets, sound institutional frameworks, and higher income levels, characteristics that may not be present in emerging markets or developing economies. These countries are shaped by varying phases of industrialisation, economic, and labour market structures. Therefore, the causal relationships uncovered in this study may not be generalised to countries outside the OECD. Future research should investigate whether similar causal dynamics between labour market variables and GDP growth exist in non-OECD countries, particularly those with varying degrees of economic development and institutional frameworks, or those susceptible to economic shocks.

Table 7 summarises the presence of pairwise causal relationships and the corresponding direction of the causality between real GDP growth, employment growth, and unemployment growth across 38 OECD countries, based on Tables 4 to 6. Unidirectional causality is the most prevalence, particularly between GDP and unemployment, which is found in 14 countries, followed by the unidirectional causality between GDP and employment in 12 countries, and between employment and unemployment in 12 countries. In the meantime, lower numbers of bidirectional causality are observed, with a mere four countries between GDP and employment in addition to six countries on GDP and unemployment. Bidirectional causality between the labour market variables (employment and unemployment) is not present at all across the member countries. The predominant unidirectional causality suggests a tendency of a one-way influence and lack of reciprocal feedback loop within the labour market and economic dynamics in most of the OECD countries.

Table 7. Types and Directions of Pairwise Causal Relationship between Real GDP Growth, Employment Growth and Unemployment Growth

Country	Presence of Causal Relationship between		
	GDP and EMP	GDP and UNE	UNE and EMP
Australia	EMP → GDP	GDP → UNE	None
Austria	GDP → EMP	GDP → UNE	None
Belgium	GDP ↔ EMP	None	UNE → EMP
Canada	None	None	None
Chile	None	GDP → UNE	EMP → UNE
Colombia	None	UNE → GDP	None
Costa Rica	None	None	None
Czech Republic	None	UNE → GDP	None
Denmark	EMP → GDP	GDP ↔ UNE	None
Estonia	None	GDP → UNE	None
Finland	None	GDP → UNE	EMP → UNE
France	GDP ↔ EMP	None	UNE → EMP
Germany	EMP → GDP	None	None
Greece	None	None	None
Hungary	None	None	None
Iceland	EMP → GDP	None	EMP → UNE
Ireland	None	None	EMP → UNE
Israel	None	None	None
Italy	GDP ↔ EMP	None	None
Japan	None	GDP ↔ UNE	None
Republic of Korea	GDP → EMP	GDP ↔ UNE	EMP → UNE
Latvia	None	None	None
Lithuania	EMP → GDP	UNE → GDP	None
Luxembourg	None	GDP → UNE	None
Mexico	None	None	UNE → EMP
Netherlands	EMP → GDP	GDP ↔ UNE	None
New Zealand	None	GDP → UNE	None
Norway	None	UNE → GDP	None
<i>Table 7 (Continued)</i>			
Poland	GDP ↔ EMP	None	UNE → EMP
Portugal	None	GDP ↔ UNE	None
Slovak Republic	None	None	None
Slovenia	EMP → GDP	UNE → GDP	UNE → EMP
Spain	None	GDP → UNE	None
Sweden	EMP → GDP	None	EMP → UNE
Switzerland	EMP → GDP	UNE → GDP	None
Türkiye	EMP → GDP	None	None
United Kingdom	None	GDP ↔ UNE	UNE → EMP
USA	None	None	None
Summary			
Unidirectional	12 countries	14 countries	12 countries
Bidirectional	4 countries	6 countries	None
None	22 countries	18 countries	26 countries

Note: GDP is the annual percentage change of real GDP at the 2010 constant price, EMP is the annual percentage change of employment, and UNE is the annual percentage change of unemployment. The single-headed arrow → represents the unidirectional causal relationship, while the double-headed arrow ↔ represents the bidirectional causal relationship.

5. Conclusion

The interconnectedness between real GDP, employment, and unemployment is fundamental as it links households and firms in a complex cycle that ultimately impacts the well-being of the economy. Understanding these linkages in the context of OECD member countries is critical to gauging the overall economic performances of these countries. This study takes a novel approach by employing the transfer entropy method to investigate the pairwise causal relationships between the variables in 38 countries based on the quarterly time series spanning the period of the third quarter of 2011 to the second quarter of 2023. Leveraging the information flow from one variable to the other, the results of transfer entropy analysis can inform the direction and strength of these causal relationships. Moreover, the application of transfer entropy is appealing to real-world data since it does not require any preliminary assumptions on data distribution and adjusts for bias in finite samples.

This study reveals varying pairwise causal relationships between real GDP, employment and unemployment in 30 OECD member countries. Taken together, the impact of employment or unemployment on economic growth emphasises the importance of appropriate policy designs and implementations for the labour market. This includes strengthening the human capital development policy and ensuring a robust social safety net and active labour market policy. On the contrary, the significant role of real GDP towards the labour market signalled the importance of mobilising efforts to bolster economic growth, among others, by maintaining stable fiscal and monetary policies, attracting more high-value-added investments and retaining good institutional governance. The bidirectional causality indicates the reciprocal effect between the labour market and the economy. Considering the nuances of the relationships, it is essential to ensure that the design and implementation of policies serve the three prongs: fostering economic growth, increasing employment opportunities, and reducing unemployment. Ultimately, this research adds value to the wealth of literature as it offers detailed findings for individual OECD member countries to guide in the formulation of more efficient economic strategies to advance sustainable development and social well-being.

Although careful attention is given in undertaking this research to safeguard the quality and interpretability of the results, it is crucial to recognise the limitations of this study. Firstly, it is found that the preliminary examination of the association between variables through Pearson product-moment correlation and distance correlation analyses cannot guarantee that transfer entropy will yield the same result. An example is New Zealand, where real GDP exhibits a unidirectional causality to unemployment, even though preliminary analyses failed to identify any linear and non-linear association between the variables. Secondly, transfer entropy cannot determine the sign of the relationship between the variables, whether an increase in one will reduce or lift the other. Thirdly, this study only investigated the pairwise relationship of labour market and economy in individual OECD member countries without regard for any external factors influencing the ties. Future research should aim to enhance methodologies, expand the scope, and include additional variables to overcome these limitations.

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Department of Mathematical Sciences
 Faculty of Science and Technology
 Universiti Kebangsaan Malaysia
 43600 UKM Bangi
 Selangor, MALAYSIA
 E-mail: p120068@siswa.ukm.edu.my*, sih@ukm.edu.my

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*Corresponding author