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Tourism Exports, Digitalisation, and Employment during the COVID-19 Pandemic: The Case of Indonesia

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Abstract: *This study aims to examine the relationship amongst tourism exports, digitalisation, and employment in tourism and allied sectors of Indonesia; and to throw light on how low-, medium, and high-skilled employment have been impacted during the coronavirus disease (COVID-19) pandemic. We include both transport service exports and travel service exports within the ambit of tourism exports. Digitalisation is defined in terms of digitally deliverable services. The study classifies employment at varying skill levels on the basis of educational qualifications, and occupation-based skill classification is used as a robustness check. The COVID-19 pandemic is captured with the help of a time dummy variable and also using the Stringency Index. The study estimates the bound testing approach to the autoregressive distributed lag (ARDL) model using quarterly time series data, and the autoregressive moving average with exogenous variable (ARMAX) model using monthly time series data, to understand the nature of the long-run relationship and short-run dynamics amongst the variables of interest. The study establishes the presence of cointegration amongst employment, tourism exports, digitalisation, and other control variables in all four cases – total employment, and low-, medium-, and high-skilled employment. We find tourism exports to have a positive and significant impact on employment, except high-skilled employment. Digitalisation of tourism exports is found to have a significant but negative impact on the total, low-skilled and medium-skilled employment. The COVID-19 pandemic is also found to have a negative and significant impact on total employment in Indonesia, with low-skilled employment being the worst affected.*

Keywords: Tourism exports, digitalisation, employment, skilled employment, COVID-19

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1. Introduction

The emergence of the digital economy is one of the biggest paradigm shifts that has occurred in international trade since the 1990s. This is evident from the phenomenal growth in the number of small commercial packages crossing international borders, facilitated by digital platforms, and service exports by contractors through labour platforms such as Amazon Mechanical Turk or Clickworker, which enable anyone who is digitally connected around the world to carry out virtual tasks (ADB et al., 2021). Several sectors, including tourism, are largely dependent on online services such as payments, deliveries, promotions, and engaging with consumers for business (Benyon et al., 2014; Kitsios et al., 2022). The coronavirus disease (COVID-19) pandemic that began in 2020 resulted in a massive disruption to the movement of people across borders, which adversely affected international trade in general and the tourism sector in particular. Tourism's share of global gross domestic product (GDP) declined from 10.4% in 2019 to 5.5% in 2020, and 62 million jobs were lost in 2020 in the travel and tourism sector (WTTC, 2021). International tourist arrivals remained deeply stunted in 2021 due to travel restrictions, the emergence of new variants of the virus, and slow vaccine administration (ADB, 2022b). However, the tourism sector recovered to a considerable extent in 2022, with a 182% increase in international tourism in the first quarter (Q1) of the year (Richter, 2022). Tourism exports constitute about 13% of global services exports, with international tourism receipts[1] comprising 84% of total tourism exports worldwide (UNWTO, 2022). The tourism sector stimulates marginal economies and promotes development through the variety of opportunities it offers for generating employment and income and promoting labour mobility. As an economic endeavour and as a sector that concentrates on leisure consumption, tourism has a compelling need for human capital in various types of jobs and sizes of operations. Characteristics such as high labour accessibility, mobility, and absorption of labour are prominent features of the tourism sector (Szivas and Riley, 1999; 2002; Szivas, Riley, and Airey, 2003).

The COVID-19 pandemic has enhanced the role of the digital economy globally, in light of social distancing norms, work-from-home arrangements, and lockdown measures (ADB et al., 2021). The Association of Southeast Asian Nations (ASEAN) experienced three kinds of economic shocks as a result of the COVID-19 pandemic. First, the region experienced negative supply shocks to international production networks. Second, the region witnessed negative demand shocks to the macroeconomy. Third, ASEAN experienced

[1] Tourism exports constitute international tourism receipts and passenger transport receipts (UNWTO, 2022).

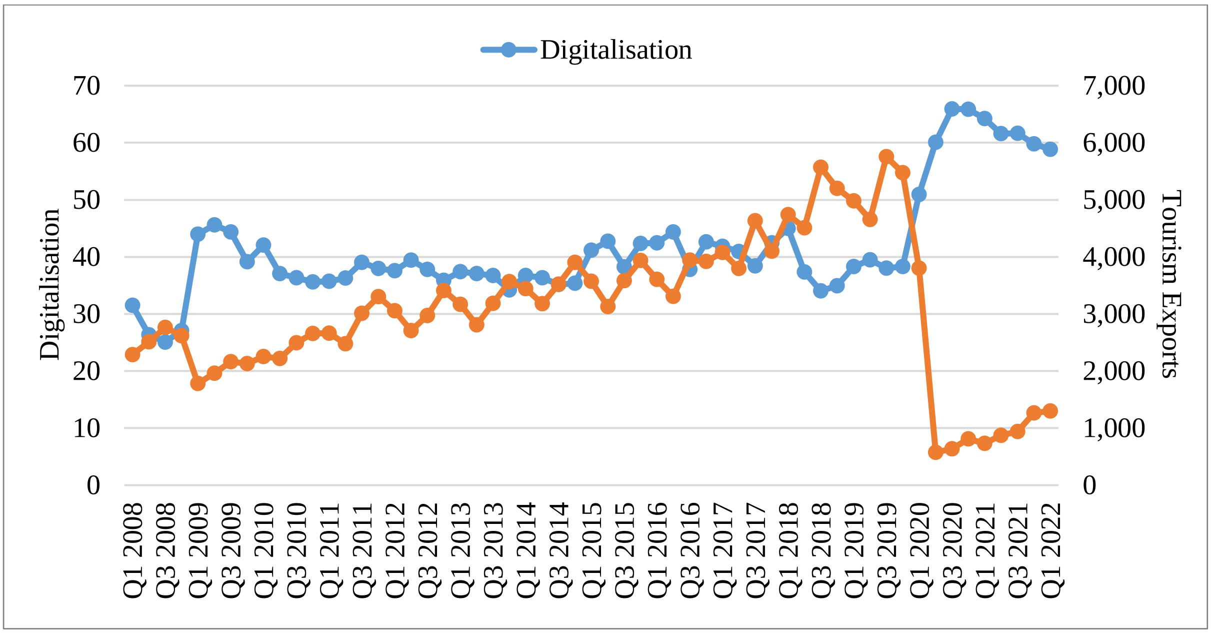
positive demand shocks for goods and services such as medical goods, information and communication technology (ICT) equipment, and internet-based services, which were required to respond to the pandemic. Although many firms in the region restructured their supply chains in response to the COVID-19 shock, very few firms undertook digitalisation of supply chains as a measure to combat the pandemic (Oikawa et al., 2021). The shortage of employees familiar with digital technologies was cited by firms as the biggest obstacle to greater digitalisation.

We consider the case of Indonesia for several reasons. Indonesia is the largest economy in Southeast Asia. It has also been the fastest growing ASEAN economy since 2018 and has the fastest growing tourism sector in the ASEAN region. Indonesia is also the world's fourth most populous nation globally and the 10th largest economy in terms of purchasing power parity. Indonesia held the G20 Presidency in 2022, with the crucial responsibility of ensuring that all member countries worked in unison to attain a stronger and more sustainable recovery from the impact of the pandemic (World Bank, 2022). Indonesia has experienced severe human costs and economic devastation because of the pandemic, with its World Bank country classification falling from upper middle-income country to lower middle-income country in 2021. Tourist arrivals boomed in Indonesia during the pre-pandemic years and were one of the main sources of foreign currency earnings (OECD, 2020). It also created approximately 13 million jobs and constituted more than 10% of the country's total employment in 2017 (OECD, 2020). The contribution of the tourism sector to Indonesia's GDP, which stood at 4.1% in 2017, rose to 5% of GDP in 2019. But it fell drastically to 2.2% of GDP in 2020, due to the pandemic (OECD, 2022). The Indonesian economy briskly rebounded from the downturn in Q3 2021 and ended the year with higher output than in 2019. It is expected to grow by 5.4% in 2022 and 5.0% in 2023, according to ADB (2022a). However, inflation is also expected to rise significantly during the same period. China, Malaysia, Singapore, and Australia are the main source countries for foreign tourist arrivals in Indonesia.

Tourism employs a large percentage of youth compared with other sectors such as mining, which employs less than 1% of youth. In developed countries such as France, close to 36% of workers in the tourism sector are aged 20–34, and across developing countries like Indonesia, 32% of workers in this sector are aged 20–34 (ILO, 2021). Low-skilled employment as well as skill gaps are prevalent in the tourism sector, which holds true for both developed and developing countries. To understand the implications of upskilling the workforce in the tourism sector, it is important to explore the relationship between digitalisation, tourism exports, and employment at varying skill levels, which is the focus of our study.

Even though Indonesia has witnessed recent innovative tourist initiatives such as ecotourism to attract foreign visitors (ILO, 2022b), the sector lacks long-term resilience strategies. Creating employment opportunities across varying skill sets and developing human capital can be a starting point towards long-run resilience. Figure 1 shows the growth trend in tourism exports and digitalisation of the Indonesian economy from 2008 to 2022. It is evident from the figure that Indonesia's tourism exports experienced a steep dip in Q1 2020 due to the outbreak of the COVID-19 pandemic, but Q2 2020 to Q1 2022 saw a gradual recovery. On the other hand, digitalisation exhibited a rising trend from Q1 2020 to Q1 2022. Given this context, this study aims to estimate the relationship amongst tourism exports, digitalisation, and employment in tourism and allied sectors of Indonesia; and elucidates how low-, medium-, and high-skilled employment have been impacted by the COVID-19 pandemic.

Figure 1: Digitalisation and Tourism Export Trends of the Indonesian Economy



Q = quarter.
Source: Authors.

2. Literature Review

The majority of traditional international trade models throw light on the relative demand for labour in an economy, but do not directly address the impact of trade on aggregate employment. Traditional theories have focused on relative wages for abundant and scarce factors of production, but they have been extended to address unemployment and underemployment as well (UNCTAD, 2018). Based on the Heckscher-Ohlin model and its offshoot Stolper-Samuelson theorem, demand for unskilled labour increases in developing countries with rising exports, as the exported products intensively utilise their abundant factor of production – unskilled labour. At the same time, developing countries experience an increase in imports of products that use skilled labour intensively. As a result, developing countries specialise in the production of unskilled labour-intensive goods and services, and create jobs for unskilled workers. The new trade theory (Krugman, 1979; 1980) allows for increasing returns to scale, which results in the emergence of large enterprises, higher labour demand, and increased specialisation. International trade increases productivity through imports of new technologies, which in turn can enhance a country's competitiveness – leading to higher production, exports, and job creation. However, due to increased productivity, fewer inputs (including labour) are required to produce a given level of output, resulting in job destruction. The new trade theory (Melitz, 2003) has proved that international trade increases the average productivity of a country, as more productive firms expand and less productive firms contract due to higher import competition.

Robbins (2003) put forth the skill-enhancing trade hypothesis, which postulates that technology transfer from developed to developing countries and greater imports of embodied technology resulting from trade liberalisation induce adaptation towards modern skill-intensive technologies in developing countries. This results in a substantial increase in domestic demand for skilled labour in developing countries. The past few decades have witnessed rapid shifts in intra-industry demand from unskilled labour towards skilled labour. Complementarity between human capital and ICT has often been cited as one of the major factors explaining this phenomenon. However, Robinson and Manacorda (1997) attributed the increased employment of high-skilled workers solely to the rapid growth in educational attainment levels of the workforce. Falk and Seim (2001) studied the impact of information technology on the employment share of high-skilled labour in the service sector. They specified the high-skilled employment share in service sector firms as a function of the information technology to output ratio, the physical capital to output ratio, export orientation, research and development (R&D) participation, and membership in a larger industrial conglomerate. They defined high-skilled labour based on educational achievement, and adopted an alternative definition of high-skilled labour based on occupation as the robustness check. Firms with a higher information technology investment to output ratio were found to employ a larger proportion of high-skilled workers. The theoretical framework put forth by Falk and Seim (2001) forms the basis of our study.

Feenstra, Ma, and Xu (2019) found that although import competition reduced jobs, export expansion created a substantial number of jobs in the United States (US). At the industry level, job gains due to US export expansion largely offset job losses due to Chinese import competition, resulting in a net gain of 379,000 jobs during 1991–2011 in their preferred estimate. Ando and Hayakawa (2022) studied the impact of the COVID-19 pandemic on international trade in services, using quarterly data from 2019 to 2020 for 146 countries. They found that the adverse impact of the pandemic on services trade was greater than that of goods trade. The nature of the impact varied across different service subsectors, with international trade in travel, transportation, and construction services, whose mode of supply involves the movement of people, bearing the brunt of the pandemic. Fitriyani and Pramana (2022) studied the impact of the COVID-19 pandemic on employment in the tourism sector in Indonesia, focusing on the Java–Bali region. Using big data extracted from job vacancy websites and other official data published by Statistics Indonesia, they carried out a descriptive analysis to study the impact of the pandemic. They found that the number of job advertisements in the tourism industry in the Java–Bali region declined during the time span of the pandemic.

Tang (2022) found that the digital economy drives tourism development and had a positive effect on tourism business and the holiday market in the United Kingdom. The tourism sector is burdened by low-skilled and low-paid jobs, adverse working conditions, and lack of career progression and job security – raising concerns about skilled work availability and sustainability in the sector (Zampoukos and Ioannides, 2011; Baum, 2015; Tsangu, Spencer, and Silo, 2017). Although high-skilled jobs were created, there was a mismatch between the educational requirements and the type of jobs, with most jobs being low-skilled, highlighting the issue of employability and job polarisation in the sector (Denny, Ooi, and Shelley, 2018). Therefore, irrespective of the number of jobs that the sector creates, there are critical inquiries about the nature of employment, human capital development, and the need for certain skill sets. When existing work undergoes digitalisation, the worst affected are workers in low- and medium-skilled jobs. High-skilled workers are brought in when there are new jobs that are being digitalised, thus creating more avenues for high-skilled employment (Balsmeier and Woerter, 2018). Cirillo et al. (2019) also found that jobs that are highly digitalised and which employ more high-skilled workers are more likely to be positively impacted by digitalisation. López González (2019) found that the adoption of simple digital tools such as web pages was relatively low amongst small and medium-sized enterprises in ASEAN Member States, constraining their ability to engage in international trade.

Our study contributes to the extant literature in several ways. Although a few existing studies have examined the impact of tourism on employment generation in Indonesia, our study brings in the novel dimension of analysing the impact of digitalisation of tourism exports on employment across varying skill levels in tourism and allied sectors of Indonesia, in the context of the COVID-19 pandemic. Our study also examines the impact of digitalisation of the Indonesian economy on high-, medium-, and low-skilled employment in tourism and allied sectors in light of the pandemic. Narayan (2021) highlighted the importance of new research on labour markets in light of the COVID-19 pandemic. Our study intends to provide crucial insights in the domain of trade policy, by estimating the long-run relationship and short-run dynamics amongst the variables of interest. The policy implications emanating from our study, pertaining to the impact of the COVID-19 pandemic on employment in tourism and allied sectors of Indonesia via the channel of tourism (service) exports and digitalisation, could possibly be extrapolated to similar countries in the ASEAN region and other emerging market economies.

3. Methodology and Data Sources

The model specification for our study, derived from the theoretical framework pertaining to employment, international trade, and digitalisation, is as follows:

$$LSEmp_t = f\,(TourX_t, Digit_t, Digit_t{*}TourX_t, PanD_t, W_t, IF_t, GCF_t, GE_t) \quad (1)$$

$$MSEmp_t = f\,(TourX_t, Digit_t, Digit_t{*}TourX_t, PanD_t\ W_t, IF_t, GCF_t, GE_t) \quad (2)$$

$$HSEmp_t = f\,(TourX_t, Digit_t, Digit_t{*}TourX_t, PanD_t\ W_t, IF_t, GCF_t, GE_t) \quad (3)$$

$$TOTEmp_t = f\,(TourX_t, Digit_t, Digit_t{*}TourX_t, PanD_t\ W_t, IF_t, GCF_t, GE_t) \quad (4)$$

All the variables specified in Equations (1) to (4) are taken in their logarithmic form. $LSEmp_t$, $MSEmp_t$, and $HSEmp_t$ in Equations (1), (2), and (3) denote the number of persons engaged in low-, medium-, and high-skilled employment in tourism and allied sectors of Indonesia, respectively. In Equation (4), the dependent variable $TOTEmp_t$ denotes the total number of persons employed in the tourism and allied sectors of Indonesia. Classification of skill-based employment into three different categories has been carried out on the basis of education to understand the differential impact on varying skill levels in employment. This study defines employment as comprising all persons of working age who, during a specified period, were in paid employment (whether at work or with a job but not at work) or self-employment (whether at work or with an enterprise but not at work), as defined by the International Labour Organization (ILO, 2022a). Quarterly time series data from Q1 2008 to Q2 2022 pertaining to Indonesia are used for estimating the above four equations. Tourism contributed only 5% to Indonesia's GDP in 2019 (OECD, 2022). Hence, we do not consider the spillover effects of tourism exports on employment in all sectors of the Indonesian economy. Quarterly employment data on 'trade, transportation, accommodation and food, and business and administrative services', available from the ILO (2022a), are taken as a proxy for employment in tourism and allied sectors. Due to constraints pertaining to the availability of quarterly employment data for the transport and travel service sectors, we have chosen a broader measure of employment. We use the quarterly employment data from the ILO, which offers the best classification we could match with the definition of tourism exports. Since our research question is not limited to studying the impact of tourism exports and employment, but also looks at the impact of digitalisation and the digitalisation of tourism exports on employment at varying skill levels in the context of the COVID-19 pandemic, choosing a broader definition of sectoral employment is further justified. Since quarterly employment data for Indonesia, both in aggregate as well as classified by skills based on education and occupation, are only available for every other quarter (Q1 and Q3) for Indonesia's tourism and allied sectors, we interpolated the data using the method proposed by de Vries et al. (2021). This interpolation method was also used for the construction of the United Nations University World Institute for Development Economics Research (UNU-WIDER) Economic Transformation Database.

The main independent variables of interest are tourism exports, denoted as $TourX_t$, and digitalisation, denoted as $Digit_t$. Quarterly data from the World Trade Organization (WTO) and the central bank of Indonesia (Bank Indonesia) on transport services exports and travel services exports (summation) for Indonesia (million US dollars) are taken as a proxy for measuring tourism exports (following the definition put forth in the International Monetary Fund's Balance of Payments Manual (IMF, 2009)). Digitalisation is defined as the use of digital technologies and data, as well as interconnection, which results in new activities or changes to existing activities (López González, 2019). UNCTAD provides annual data on various measures of the digital economy, such as ICT goods as a share of total trade, core indicators of ICT use in business, international trade in digitally deliverable services, and international trade in ICT services. However, UNCTAD does not provide quarterly data on any of these variables. Since quarterly data on imports of 'digitally deliverable services' and total services imports are available for Indonesia from the WTO, the 'ratio of digitally deliverable services imports to total services imports (in percentages)' is taken as the measure of digitalisation, following the definition put forth by UNCTAD (2015) and Obashi and Kimura (2020). This indicator reflects the degree to which the country utilises ICTs to reduce the service-link cost. Digitally deliverable services comprise telecommunication services, insurance and pension services, financial services, computer and information services, charges for the use of intellectual property, and other business services, as per IMF (2009). $Digit_t * TourX_t$ denotes the interaction term between tourism exports and digitalisation, which represents the extent of digitalisation of the tourism sector. Digitalisation helps the tourism sector penetrate international markets without having a large physical presence but having significant transnational characteristics (Zhan, 2021). A dummy variable, $PanD_t$, is included in the model to capture the impact of the COVID-19 pandemic. The dummy variable takes a value of 1 for quarterly data beginning from Q1 2020, and 0 for the preceding quarters.

The vector of control variables entering the model specifications (1) to (4) includes wages, inflation, private investment, and government expenditure. W is wages in Indonesia, measured in thousand US dollars. Wages are the mean monthly earnings across all skill levels, and are defined as the gross remuneration paid to employees regularly, for time worked and not worked together. These earnings include severance and termination pay (ILO, 2021). IF is the inflation rate based on the Consumer Price Index (CPI), and GE is the government final consumption expenditure, measured as a percentage of GDP. GCF is fixed capital formation in the private sector, which is a proxy for private investment. Nominal wages and government final consumption expenditure have been deflated using the GDP deflator, which is standard practice in the literature. Gross fixed capital formation has not been deflated since it is rarely affected by domestic inflation. Tourism exports have not been deflated since they are a service export for which finding the appropriate deflator is problematic. Unit value indices of exports are often used to deflate merchandise exports, which are unavailable for service exports. The control variables are selected based on the literature on the determinants of employment and skill-based employment (Freeman and Schettkat, 2000; Huttunen, Pirttilä, and Uusitalo, 2013; Kertesi and Köllö, 2003; Rama, 2001; Autor and Dorn, 2013; Bekhet, 2010; Aiyagari, Christiano, and Eichenbaum, 1992; Verbič, 2000).

Employment levels in an economy are a function of aggregate demand, which in turn is dependent on both government expenditure and private investment (Hawtrey, 1925). Government expenditure on basic infrastructure and the social sector has a positive multiplier effect on employment. Keynes (1936) provided the theoretical basis for the inclusion of government expenditure as a control variable for this study. Keynesian theory postulates that government expenditure can boost employment generation and bring an economy out of a recession. On the other hand, Abrams (1999) provided conceptual and empirical evidence in support of higher government expenditure leading to higher unemployment rates. Kalecki (1945) proved that stimulating private investment can maintain full employment of an economy only if the interest rate declines continuously, income tax is reduced continuously, and subsidies for private investment are increased continuously. The Philips curve highlights the existence of an inverse relationship between inflation and unemployment. The higher the prevailing inflation rate in an economy, the lower the unemployment rate, implying greater job creation. The occurrence of stagflation in the 1970s contradicted the Philips curve, with many countries experiencing both a high inflation rate and a high unemployment rate at the same time. Wages play a central role in determining employment, as reflected in the factor demand equation. Neoclassical theory postulates an inverse relationship between real wages and employment. Given a fixed capital stock, the marginal product of labour declines as extra workers are hired. Hence, firms will demand a higher number of workers only if the fall in real wages compensate for the decline in the marginal product of the last worker, when more workers are employed.

Data sources for all the dependent and independent variables used in this study are detailed in Table 1.

Table 1: Data Sources and Variable Descriptions

Variable	Description	Data source
LSEmp ('000)	Number of employees with basic and less than basic educational qualifications	ILO
MSEmp ('000)	Number of employees with intermediate educational qualifications	ILO
HSEmp ('000)	Number of employees with advanced educational qualifications	ILO
TOTEmp ('000)	Number of employees across all levels of educational qualifications	ILO
W ($)	Mean wage earnings across all skill levels	ILO
TourX ($)	Tourism exports	WTO
Digit (%)	Digitally deliverable service imports as a share of total service imports, as defined by UNCTAD (2015) and Obashi and Kimura (2020)	WTO
GE ($)	Government final consumption expenditure	International Financial Statistics (IMF)
PanD (dummy variable)	Presence of COVID-19 pandemic	
IF (%)	CPI-based inflation	Statistics Indonesia
GCF ($)	Gross fixed capital formation	International Financial Statistics (IMF)
LOEmp ('000)	Number of employees in low-skilled occupations	ILO
MOEmp ('000)	Number of employees in medium-skilled occupations	ILO
HOEmp ('000)	Number of employees in high-skilled occupations	ILO
TOCEmp ('000)	Number of employees in all types of occupations	ILO
FTA ('000)	Number of international tourist arrivals (monthly)	Statistics Indonesia
STRIN (Index)	Stringency Index reflecting governments' responses to the COVID-19 pandemic	Oxford COVID-19 Government Response Tracker

COVID-19 = coronavirus disease, CPI = consumer price index, ILO = International Labour Organization, IMF = International Monetary Fund, WTO = World Trade Organization.
Source: Authors.

For the robustness tests, the set of dependent variables pertaining to employment across varying skill levels, classified based on education levels, is replaced with variables denoting employment across varying skill levels, classified based on occupations. Employment, classified according to education levels, is based on the International Standard Classification of Education, whereas the employment classified according to occupations is based on the ILO's International Standard Classification of Occupations (1: low-skilled; 2: medium-skilled; and 3 and 4: high-skilled).

4. Estimation Strategy

We undertake a quarterly time series estimation and monthly time series estimation as part of this study. First, we examine the long-run relationship and short-run dynamics between the variables of interest in Equations (1) to (4), with the help of cointegration techniques and an error correction model. Stationarity tests such as the Augmented Dickey-Fuller (ADF) test are carried out to check the unit root properties of the variables. We use an autoregressive distributed lag (ARDL) model with quarterly data to estimate the impact of tourism exports and digitalisation on employment in tourism and allied sectors of Indonesia. We use the ARDL approach to cointegration for different reasons. The ARDL approach can be applied even if the order of integration of the variables entering the regression equation is a mix of I(O) and I(1). The Wald test underlying the procedure, in addition to being in a generalised Dickey-Fuller type regression, tests the significance of the lagged variables in a conditional unrestricted equilibrium correction model (Pesaran, 1997; Pesaran and Shin, 1999; Pesaran, Shin, and Smith, 2001). The ARDL bound testing approach to cointegration is also unbiased and efficient in small samples. It allows for the estimation of short- and long-run coefficients and removes problems of omitted variables and autocorrelation. As opposed to the Engle and Granger (1987) and Johansen (1988) techniques of cointegration, Pesaran and Shin (1999) expounded that the ARDL framework uses ordinary least squares (OLS) estimators of the short-run parameters, and the estimators are consistent across time. The long-run ARDL estimators are also super consistent in small sample sizes.

The bound testing representation of the ARDL model for the total employment model specification, as per Equation (4), is elaborated in Equation (5).

$$\Delta TOTEmp_t = \alpha_0 + \sum_{i=1}^{n1} \alpha_{1i} \Delta TOTEmp_{t-i} + \sum_{i=0}^{n2} \alpha_{2i} \Delta TourX_{t-i} + \sum_{i=0}^{n3} \alpha_{3i} \Delta Digit_{t-i} + \sum_{i=0}^{n4} \alpha_{4i} \Delta Digit * TourX_{t-i} + \sum_{i=0}^{n5} \alpha_{5i} \Delta PanD_{t-i} + \sum_{i=0}^{n6} \alpha_{6i} \Delta W_{t-i} + \alpha_7 \sum_{i=0}^{n7} \alpha_{7i} \Delta IF_{t-i} + \sum_{i=0}^{n8} \alpha_{8i} \Delta GCF_{t-i} + \sum_{i=0}^{n9} \alpha_{9i} \Delta GE_{t-i} + \alpha_{10}\ TOTEmp_{t-1} + \alpha_{11}\, TourX_{t-1} + \alpha_{12}\, Digit_{t-1} + \alpha_{13}\, Digit * TourX_{t-1} + \alpha_{14} PanD_{t-1} + \alpha_{15}\, W_{t-1} + \alpha_{16}\, IF_{t-1} + \alpha_{17}\, GCF_{t-1} + \alpha_{18}\, GE_{t-1} + u_t \qquad (5)$$

The bound testing representation of the ARDL models for high-, medium,- and low-skilled employment as per Equations (1), (2), and (3) can be written in a similar fashion as Equation (5), by replacing the *TOTEmp* variable with the *HSEmp, MSEmp,* and *LSEmp* variables, respectively.

For the monthly estimation, we adopt a two-step procedure, following Gharehgozli et al. (2020). Although Gharehgozli et al. (2020) used a two-step vector autoregression (VAR) for their study, we do not resort to VAR in this study due to the unit root and cointegration properties of our data. As the first step of the monthly estimation, the effect of the COVID-19 pandemic on Indonesia's tourism exports is forecast. We use monthly data on foreign tourist arrivals in Indonesia as a measure of tourism exports, in an autoregressive moving average with exogenous variable (ARMAX) model. ARMAX is introduced in this study to better capture the impact of tourism exports and digitalisation on employment during the COVID-19 pandemic. While carrying out an econometric estimation using actual quarterly time series data of tourism export receipts (million US dollars), we have the limitation of being able to capture the impact of the COVID-19 pandemic only with the help of a dummy variable that takes the value of 1 from Q1 2020 and 0 for preceding quarters. By estimating the ARMAX model using monthly data to study the impact of the Oxford Stringency Index (*STRIN*) on foreign tourist arrivals (*FTA*) in Indonesia, we can obtain forecast values for tourism exports for the period from Q1 2020 to Q1 2022. This helps us capture the impact of the COVID-19 pandemic on employment (via the channel of tourism exports) using one more indicator – the Oxford Stringency Index.

The specification for the ARMAX model is as follows:

$$FTA_t = STRIN_t \beta + \sum_{i=1}^{p} \rho_i (FTA_{t-i} - STRIN_{t-i} \beta) + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad (6)$$

In Equation (6), some of the ρ_i and θ_j may be constrained to 0.

Monthly data on the Stringency Index, published by Oxford University Coronavirus Government Response Tracker, are used to capture the pandemic. The nine metrics used to calculate the Stringency Index are school closures, workplace closures, cancellation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movements, and international travel controls. This composite index records the strictness of the government policies of a country. Owing to the availability of COVID-19 data, the monthly time series is from the first month (M1) of 2020 to M3 2022. The ARMAX approach is used with the pandemic (*STRIN*) as the exogenous variable, and the effect of a change in the pandemic is propagated over time through the persistence of arrivals of foreign tourists. This also helps us capture the data variation in a short time series and measure the magnitude of the pandemic shocks that the variables have encountered recently in a more precise manner. As the second step, we include the quarterly computations of the monthly forecasts of foreign tourist arrivals in the tourism exports quarterly data from M1 2020 to M3 2022, and redo the quarterly estimation with employment.

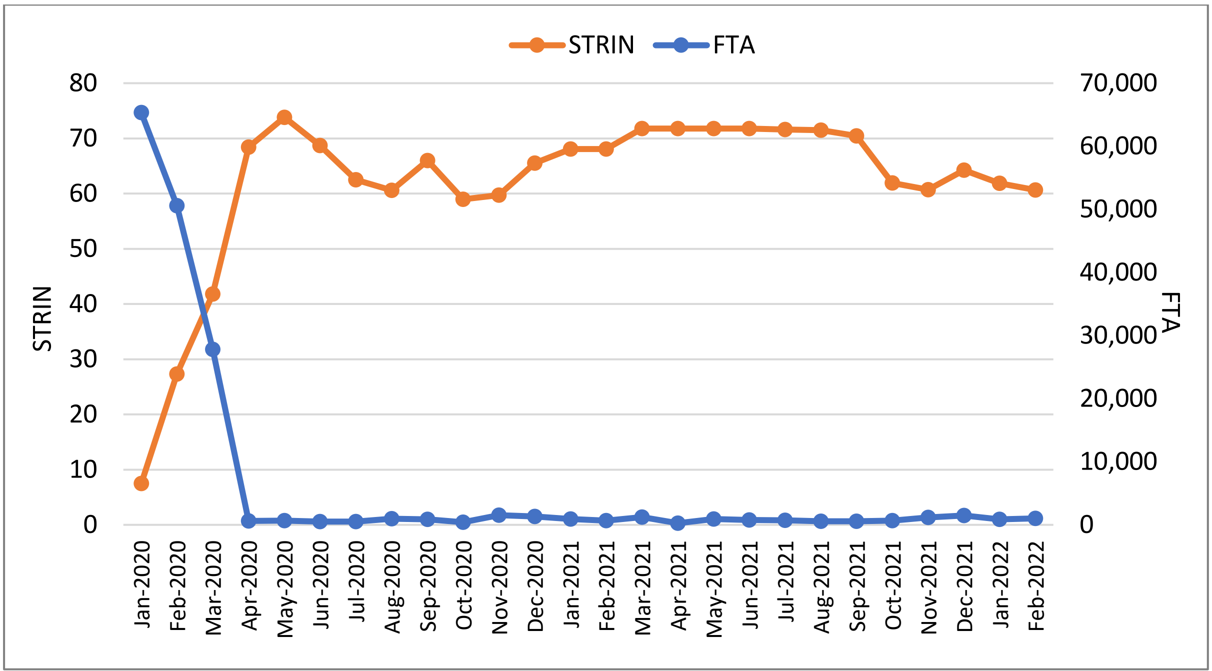
5. Empirical Results and Discussion

We present the descriptive statistics of all the variables considered for the quarterly and monthly estimations in Table 2. The summary statistics indicate that the average number of workers in low-skilled employment in tourism and allied sectors of Indonesia is quite high compared with medium- and high-skilled employment, when the workforce is classified according to varying skill levels based on education. However, when the workforce is classified according to varying skill levels based on occupation, the average number of workers in medium-skilled employment is found to be much higher than that of low- and high-skilled employment. This indicates the presence of skill mismatches between education and occupation amongst the workers employed in tourism and allied sectors of Indonesia.

The correlation matrix (Table 8) indicates a reasonable correlation between the variables considered, justifying the choice of independent variables entering the ARDL model. The correlation between the two variables considered for the monthly ARMAX estimation – foreign tourist arrivals and the Stringency Index – is highly negative, reinforcing the need for our two-step estimation procedure.

By the beginning of 2022, foreign tourist arrivals to Indonesia increased, coinciding with the COVID-19 pandemic (proxied by the Oxford Stringency Index) slightly altering its course (Figure 2). The two data series share highly negative covariance, indicating that foreign tourist arrivals reduced significantly during the pandemic. Before forecasting, we examined the stationarity of the monthly data with the ADF test (Table 2). We find that both the series entering the ARMAX model are stationary and do not follow a white noise process.

Figure 2: Indonesia's Stringency Index and Foreign Tourist Arrivals



M = month.
Source: Authors.

The impact of tourism exports and digitalisation on low-skilled, medium-skilled, high-skilled, and total employment in tourism and allied sectors of Indonesia is estimated; and the long-run relationship and short-run dynamics are estimated and reported in Tables 4, 5, and 6. Two sets of ARDL models are estimated – one with actual quarterly data and the inclusion of the pandemic dummy (Table 6) and another based on ARMAX forecasts and without the inclusion of the pandemic dummy (Table 4).

Prior to the ARDL estimation, we test for stationarity of our quarterly data with the ADF unit root test. The ADF test results are reported in Table 2. We find that most of the variables become stationary at first difference, and a few others (e.g. inflation) are stationary in the level form. The F-test results based on the ARDL bound testing approach to cointegration reported in Table 3 indicate the presence of a long-run equilibrium relationship amongst employment, digitalisation, and tourism exports in all four cases. The negative and statistically significant error correction term in Table 4 reinforces the presence of cointegration amongst the variables of interest. Table 4 also reports the long-run coefficients derived from the ARDL model, based on ARMAX forecasts and skilled employment classified according to education. The long-run coefficient of tourism exports is found to be positive and statistically significant in all the models in Table 4, except in the case of high-skilled employment. Since all the variables have been taken in logarithmic form in the regression estimation, all other things being equal, we can conclude that a 1% increase in tourism exports is found to result in an increase of about 12% in low-skilled employment, compared with a rise of only 8% in both medium-skilled and total employment in tourism and allied sectors of Indonesia. While digitalisation is found to have a negative impact on low-skilled, medium-skilled, and total employment, the long-run coefficient of the tourism exports–digitalisation interaction term exhibits heterogenous effects across skill levels. In the case of total employment, as well as low- and medium-skilled employment, the coefficient of the interaction term is negative and statistically significant. This coincides with a positive yet statistically insignificant coefficient in the case of high-skilled workers. This indicates a fall in employment generation amongst workers with low and medium education levels when tourism exports get digitalised, as opposed to greater employment generation amongst high-skilled employees who have acquired advanced levels of education.

The short-run results present mixed evidence on the relationship amongst tourism exports, digitalisation, and employment. The short-run coefficients derived from the ARDL model, based on ARMAX forecasts and skilled employment classified according to education, are reported in Table 5. The impact of tourism exports on employment is uneven in the short run, as indicated by the positive and statistically significant coefficient of tourism exports in the case of high-skilled employment. The short-run coefficients of digitalisation and the tourism exports–digitalisation interaction term are positive for employees with low and medium levels of education and the total number of employees. These coefficients are positive and statistically significant, particularly in the case of low-skilled employees. This indicates that the sector favours low-skilled workers over medium- or high-skilled workers. The cumulative sum (CUSUM) of recursive residuals test results, which provide information relating to the stability of the estimated ARDL models, are reported in Figures 3, 4, 5, and 6.

The impact of the control variables on employment also presents mixed evidence. In the long run, a rise in real wages is found to have a negative and significant impact on total employment and low-skilled employment, but an insignificant impact on medium-skilled employment. However, for high-skilled employment in the long run and employment across all levels in the short run, wages have a positive impact (Rama, 2001; Kertesi and Köllö, 2003). Inflation is found to have a positive but insignificant impact on employment across all skill levels. Government expenditure is found to have a positive impact on employment across skill levels (except high-skilled employment) in the long run. In the case of low-skilled employment, the impact of government expenditure is found to be positive and statistically significant. A rise in private investment increases high-skilled employment in the long run, but has a negative and significant impact on low-skilled and total employment. The empirical results indicate that in the long run, private investment tends to favour employment generation of high-skilled workers because of their revenue-generating capacity and human capital (Meyer and Sanusi, 2019).

The ARDL model estimated using actual quarterly data, with the impact of the COVID-19 pandemic being captured with the help of a dummy variable, is reported in Table 6. The presence of cointegration is found in the case of all four models in Table 6, as is evident from the negative and significant error correction term. Tourism exports are found to have a positive impact on employment across all skill levels in the long run, but turn out to be statistically significant only in the case of low-skilled employment. The digitalisation of tourism exports is found to have a negative impact on employment across all skill levels in the long run, but this coefficient also turns out to be statistically significant only in the case of low-skilled employment. The digitalisation of the Indonesian economy is also found to have a negative but insignificant impact on employment across varying skill levels in Indonesia's tourism and allied sectors. The estimation results based on actual data are in alignment with the results based on ARMAX forecasts, except in the case of high-skilled employment. The pandemic dummy is found to be negative in the case of employment across all skill levels, and turns out to be statistically significant in the case of low-skilled employment and total employment.

As a robustness test, we replaced the dependent variable used in Equations (1) to (4), which is employment classified according to education levels, with employment classified according to occupation levels – *LOEmp, MOEmp, HOEmp*, and *TOCEmp*. The robustness test results using employment based on occupations as dependent variables, reported in Table 7, also indicate the presence of cointegration amongst the variables of interest. None of the long-run coefficients pertaining to tourism exports, digitalisation, and their interaction term are significant. The signs of the long-run coefficients based on occupation are also not found to be in alignment with the long-run coefficients based on education, in the case of most of the explanatory variables. These differences could be attributed to the prevalence of mismatches in the Indonesian labour market between the educational background of workers and their occupations, as evident from the study by Sukanti and Sulistyaningrum (2022). Another possible explanation could be the existence of skill mismatches in the Indonesian labour market, as highlighted earlier in the summary statistics. When classified in terms of education, most Indonesian workers belong to the category of low-skilled employment (with basic education). When classified in terms of occupation, most Indonesian workers belong to the category of medium-skilled employment.

6. Conclusion and Policy Implications

This study is motivated by the fall in tourism exports and rise in digitalisation induced by the COVID-19 pandemic, and their impact on employment across varying skill levels in tourism and allied sectors of Indonesia. In this context, the employment–tourism exports–digitalisation relationship is explored with respect to low-skilled, medium-skilled, high-skilled, and total employment.

The results (based on ARDL–ARMAX forecasts) of this study pertaining to the positive and significant impact of tourism exports on employment (except high-skilled) align with the results from earlier research on tourism and employment generation (e.g. Manzoor et al., 2019). The results pertaining to the negative and significant impact of digitalisation of tourism exports on employment for low-skilled, medium-skilled, and total employment also aligns with the results of earlier research (Balsmeier and Woerter, 2019; Cirillo et al., 2019). Further, we find empirical evidence supporting the neoclassical economic theory which postulates a decline in employment with an increase in real wages, especially given that most of the firms engaged in the tourism business are small and medium-sized. The impact of tourism exports and digitalisation on high-skilled employment is found to be an outlier. Although cointegration exists between the variables of interest, the long-run coefficients are found to be statistically insignificant in the case of high-skilled employment. When ARDL estimation was carried out using actual quarterly data, the COVID-19 pandemic dummy turned out to be negative for employment across skill levels. It was statistically significant for low-skilled employment and total employment. Hence, empirical evidence underlines the fact that the COVID-19 pandemic had an adverse impact on aggregate employment in tourism and allied sectors of Indonesia, but the low-skilled workers in these sectors were the worst affected by the pandemic.

Tourism exports are found to have a positive and statistically significant impact on total, low-skilled, and medium-skilled employment in tourism and allied sectors of Indonesia.

Policies should be formulated to boost the employment potential of the tourism sector, in the light of Goal 8 of the United Nations Sustainable Development Goals (SDGs). Targeted tourism promotion campaigns could be undertaken in developed and developing countries, catering to the differences in income, seasonality of travel, tastes, and preferences of the customers. Market research on these dimensions would be helpful in designing such promotion campaigns. Steps towards showcasing Indonesia as a hub for spiritual and wellness tourism could be undertaken to attract foreign tourists. In addition to popular destinations such as Bali, other Indonesian provinces that could emerge as spiritual and wellness hubs need to be identified. Improvements in infrastructure, maintenance of law and order, and the provision of basic civic amenities – from cities to ports to tourist destinations – could go a long way in boosting foreign tourist inflows to Indonesia. Developing rural and forested areas of Indonesia as centres of ecotourism, and developing the skills of the rural population in this domain, could also prove helpful in boosting sustainable tourism in Indonesia.

Digitalisation in general, and digitalisation of tourism exports in particular, are found to have a negative impact on low-skilled, medium-skilled, and total employment in tourism and allied sectors. The impact of digitalisation is found to be positive but insignificant on high-skilled employment. The government can focus on upskilling employees and building technological capacity in tourism and allied sectors to reap benefits from the digital economy. Digitalisation of tourism has skyrocketed in the last couple of years and therein lies the future of the sector. The tourist experience could be enriched with new technologies such as the metaverse, augmented reality, and mixed reality, which allow travellers to experience things like 3D hotel tours and amenities at tourist destinations before actual visits. OECD (2021) highlighted the importance of embracing digitalisation through the tourism ecosystem to build back resilient business in the post-COVID-19 era. Exploiting avenues for marketing and product and destination development, and investing in human capital and skills, are crucial for digital transformation of this sector. There remains immense untapped potential in Indonesia's tourism and allied sectors for employment generation and decent work for all, and informed government policies can help in achieving Goal 8 of the SDGs.

Table 2: Descriptive Statistics and ADF Unit Root Test Results

Variable	Obs	Mean	Std. dev.	Min	Max	ADF
LSEmp	56	-0.002	0.038	-0.191	0.074	-3.025
MSEmp	56	0.034	0.122	-0.027	0.887	-2.847
HSEmp	56	0.019	0.054	-0.107	0.216	-0.441
LOEmp	52	-0.003	0.094	-0.583	0.127	-1.934
MOEmp	52	0.011	0.046	-0.131	0.251	-0.492
HOEmp	52	0.017	0.229	-1.104	1.039	-3.234
TOTEmp	56	0.009	0.025	-0.033	0.074	-0.301
TOCEmp	52	0.009	0.024	-0.033	0.074	-0.32
TourX	56	-0.014	0.379	-2.546	0.776	-1.633
Digit	56	0.011	0.106	-0.186	0.485	-1.32
W	56	0.005	0.052	-0.077	0.240	-2.173
IF	56	1.145	1.055	-0.430	4.440	-6.558***
GE	56	0.004	0.029	-0.045	0.077	-2.765
GCF	56	0.013	0.056	-0.098	0.130	-3.625
PanD	56	0.143	0.353	0.000	1.000	-0.379
FTA	27	7.118	1.390	5.572	11.087	-7.311***
STRIN	27	7.445	0.605	4.605	7.736	-6.248***

ADF = Augmented Dickey-Fuller.
Note: *** indicates rejection of the null hypothesis of the ADF test of presence of unit root, at the 1% level of significance.
Source: Author.

Table 3: F-Statistics for ARDL Bounds Test for Cointegration and Critical Value Bounds for F-Statistic

k(7)	F-statistic						
LSEmp	9.592	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
		90%	90%	95%	95%	99%	99%
		2.03	3.13	2.32	3.5	2.96	4.26
MSEmp	5.549	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
		90%	90%	95%	95%	99%	99%
		2.03	3.13	2.32	3.5	2.96	4.26
HSEmp	6.962	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
		90%	90%	95%	95%	99%	99%
		2.03	3.13	2.32	3.5	2.96	4.26
TOTEmp	11.062	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
		90%	90%	95%	95%	99%	99%
		2.03	3.13	2.32	3.5	2.96	4.26

ARDL = autoregressive distributed lag.
Note: F > critical value at I(1): Reject H_0 of absence of cointegration.
Source: Authors.

Table 4: ARDL Estimation of Long-Run Coefficients and Error Correction Term for Models 1, 2, 3, and 4 (Based on Education and ARMAX Forecasts)

Variable	*LSEmp*	*MSEmp*	*HSEmp*	*TOTEmp*
ECT				
(-1)LSEmp	-1.635***			
	[0.211]			
(-1)MSEmp		-1.201***		
		[0.204]		
(-1)HSEmp			-0.762**	
			[0.281]	
(-1)TOTEmp				-1.564***
				[0.183]
LR				
TourX	0.118***	0.088**	-0.301	0.088***
	[0.030]	[0.037]	[0.263]	[0.025]
Digit	-0.074*	-0.055	0.229	-0.071*
	[0.042]	[0.052]	[0.364]	[0.035]
*TourX * Digit*	-0.803***	-0.601**	3.526	-0.603***
	[0.213]	[0.267]	[2.187]	[0.179]
W	-0.265***	-0.147	0.09	-0.189***
	[0.076]	[0.091]	[0.548]	[0.063]
IF	0.0003	0.0004	0.0003	0.0006
	[0.003]	[0.003]	[0.018]	[0.002]

Variable	*LSEmp*	*MSEmp*	*HSEmp*	*TOTEmp*
GE	0.277*	0.177	-0.608	0.184
	[0.146]	[0.168]	[1.062]	[0.118]
GCF	-0.220*	-0.161	0.524	-0.199**
	[0.113]	[0.136]	[0.902]	[0.093]

ARDL = autoregressive distributed lag, ARMAX = autoregressive moving average with exogenous variable, ECT = error correction term.
Notes: ***,**,and * indicates 1%, 5%, and 10% level of statistical significance. Values in parentheses are standard errors.
Source: Authors.

Table 5: ARDL Estimation of Short-Run Coefficients for Models 1, 2, 3, and 4 (Based on Education and ARMAX Forecasts)

Variable	*LSEmp*	*MSEmp*	*HSEmp*	*TOTEmp*
TourX	-0.092*	-0.014	0.292*	-0.049
	[0.047]	[0.043]	[0.162]	[0.038]
(-1)TourX	-0.045	0.018	0.398*	-0.01
	[0.032]	[0.029]	[0.193]	[0.026]
(-2)TourX			0.177	
			[0.156]	
Digit	0.148**	0.074	-0.244	0.115**
	[0.055]	[0.050]	[0.220]	[0.044]
(-1)Digit	0.078**	0.023	-0.259	0.049*
	[0.032]	[0.030]	[0.161]	[0.026]
(-2)Digit			-0.019	
			[0.090]	
*TourX * Digit*	0.689**	0.195	-3.004**	0.411
	[0.298]	[0.270]	[1.261]	[0.244]
*(-1)TourX * Digit*	0.334*	-0.05	-3.262**	0.119
	[0.179]	[0.163]	[1.222]	[0.147]
*(-2)TourX * Digit*			-1.495	
			[0.903]	
W	0.227**	0.071	0.272	0.169**
	[0.106]	[0.090]	[0.363]	[0.079]
(-1)W	0.246***	0.049	-0.108	0.153**
	[0.084]	[0.071]	[0.288]	[0.062]
(-2)W			-0.253	
			[0.219]	
IF	0.0002	-0.003	-0.005	-0.003
	[0.004]	[0.003]	[0.013]	[0.003]
(-1)IF	-0.002	-0.003	0.011	-0.002
	[0.003]	[0.002]	[0.012]	[0.002]
(-2)IF			0.011	
			[0.009]	
GE	-0.003	0.207	1.207	0.156

Variable	*LSEmp*	*MSEmp*	*HSEmp*	*TOTEmp*
	[0.238]	[0.201]	[0.909]	[0.181]
(-1)GE	0.124	0.012	-0.279	0.076
	[0.163]	[0.141]	[0.902]	[0.127]
(-2)GE			-0.457	
			[0.475]	
GCF	0.022	-0.266	-1.156*	-0.109
	[0.182]	[0.164]	[0.642]	[0.142]
(-1)GCF	-0.054	-0.137	-0.177	-0.069
	[0.128]	[0.116]	[0.703]	[0.103]
(-2)GCF			0.337	
			[0.441]	
(-1)LSEmp	0.808***			
	[0.165]			
(-1)MSEmp		0.320**		
		[0.147]		
(-1)HSEmp			0.256	
			[0.199]	
(-2)HSEmp			0.016	
			[0.212]	
(-1)TOTEmp				0.683***
				[0.137]
Constant	0.007	0.019***	0.026	0.017***
	[0.005]	[0.006]	[0.016]	[0.005]

ARDL = autoregressive distributed lag, ARMAX = autoregressive moving average with exogenous variable.
Source: Authors.

Table 6: ARDL Estimation of the Long-Run Coefficients for Models 1, 2, 3, and 4 (Based on Education and Actual Data) – With Pandemic Time Dummy

Variable	***LSEmp***	***MSEmp***	***HSEmp***	***TOTEmp***
ECT				
LSEmp(-1)	-1.506***			
	[0.199]			
MSEmp(-1)		-0.844***		
		[0.182]		
HSEmp(-1)			-0.628***	
			[0.185]	
TOTEmp(-1)				-1.610***
				[0.245]
LR				
TourX	0.230***	0.057	0.346	0.095
	[0.068]	[0.075]	[0.381]	[0.064]
Digit	-0.04	-0.01	-0.146	-0.054
	[0.044]	[0.069]	[0.269]	[0.040]
*TourX*Digit*	-1.022**	-0.195	-2.053	-0.609
	[0.419]	[0.393]	[2.087]	[0.413]
W	-0.197**	-0.234**	0.006	-0.178**
	[0.071]	[0.109]	[0.443]	[0.065]
IF	0	0.001	0.022	-0.001
	[0.003]	[0.004]	[0.022]	[0.003]
GE	0.309*	0.298	-0.542	0.161
	[0.165]	[0.293]	[1.122]	[0.147]
GCF	-0.241*	-0.28	0.072	-0.167
	[0.122]	[0.212]	[0.841]	[0.110]
PanD	-0.021***	-0.007	-0.015	-0.016***
	[0.006]	[0.010]	[0.041]	[0.005]

ARDL = autoregressive distributed lag.
Source: Authors.

Table 7: ARDL Estimation of Long-Run Coefficients and Error Correction Term for Models 1, 2, 3, and 4
(Based on Occupation and ARMAX Forecasts)

Variable	*LOEmp*	*MOEmp*	*HOEmp*	*TOCEmp*
ECT				
(-1)LOEmp	-1.532***			
	[0.290]			
(-1)MOEmp		-1.456***		
		[0.233]		
(-1)HOEmp			-1.528***	
			[0.214]	
(-1)TOCEmp				-1.559***
				[0.230]
LR				
TourX	-0.345	0.074	0.014	0.009
	[0.415]	[0.203]	[0.861]	[0.085]
Digit	-0.186	0.046	0.179	0.093
	[0.493]	[0.239]	[1.021]	[0.095]
*TourX * Digit*	2.049	-0.652	0.003	-0.099
	[2.828]	[1.371]	[5.828]	[0.592]
W	-1.149	0.639*	-2.031	0.063
	[0.852]	[0.367]	[1.585]	[0.144]
IF	0.04	-0.029**	0.08	-0.007
	[0.026]	[0.012]	[0.050]	[0.005]
GE	0.344	-0.832	-0.618	-0.658*
	[1.647]	[0.760]	[3.314]	[0.327]
GCF	0.788	0.393	1.743	0.653**
	[1.136]	[0.530]	[2.310]	[0.233]

ARDL = autoregressive distributed lag, ARMAX = autoregressive moving average with exogenous variable.
Source: Authors.

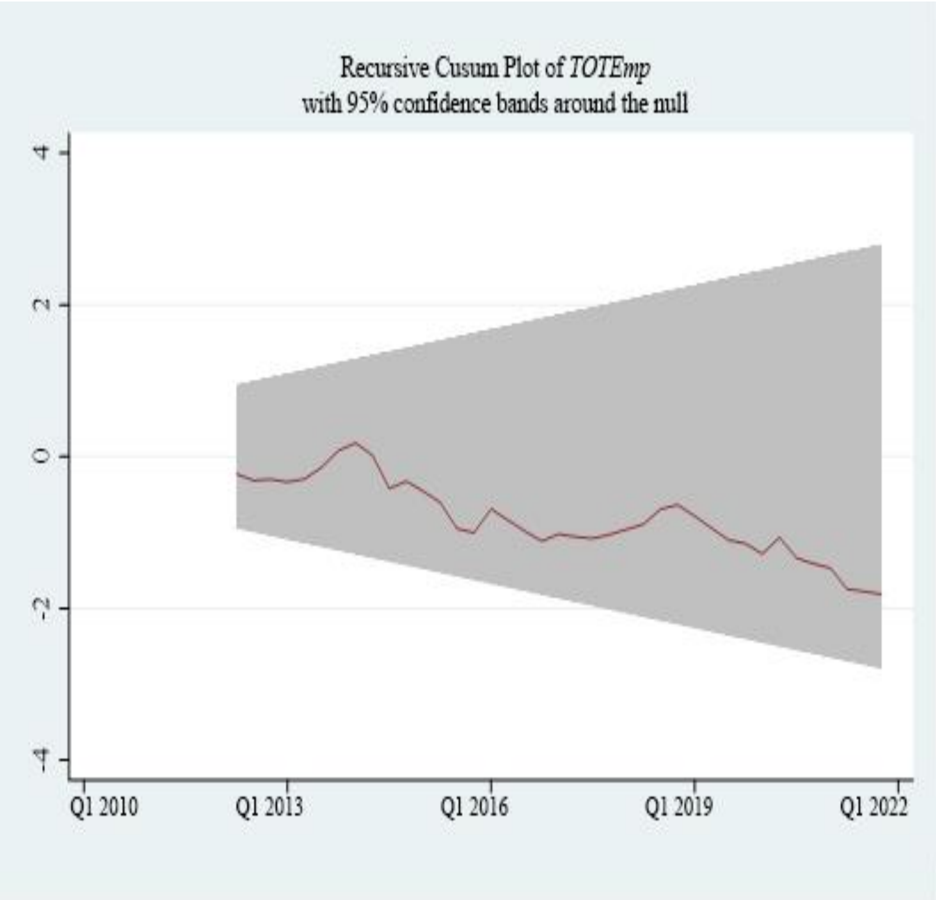
Table 8: Correlation Matrix

Variable	*LSEmp*	*MSEmp*	*HSEmp*	*LOEmp*	*MOEmp*	*HOEmp*	*TOTEmp*	*TOCEmp*	*TourX*	*Digit*	*W*	*IF*	*GE*	*GCF*	*PanD*
LSEmp	1.000														
MSEmp	0.908	1.000													
HSEmp	0.859	0.978	1.000												
LOEmp	-0.612	-0.601	-0.596	1.000											
MOEmp	0.879	0.941	0.906	-0.739	1.000										
HOEmp	0.286	0.477	0.518	0.067	0.271	1.000									
TOTEmp	0.940	0.995	0.975	-0.616	0.940	0.450	1.000								
TOCEmp	0.852	0.969	0.947	-0.556	0.946	0.552	0.957	1.000							
TourX	0.308	0.217	0.255	-0.227	0.241	0.236	0.252	0.267	1.000						
Digit	0.409	0.568	0.533	-0.286	0.508	0.202	0.535	0.518	-0.623	1.000					
W	0.770	0.920	0.942	-0.606	0.899	0.509	0.909	0.934	0.359	0.405	1.000				
IF	-0.391	-0.381	-0.393	0.344	-0.353	-0.147	-0.394	-0.336	-0.006	-0.314	-0.319	1.000			
GE	0.715	0.886	0.877	-0.335	0.797	0.543	0.862	0.886	0.130	0.547	0.868	-0.285	1.000		
GCF	0.780	0.920	0.930	-0.443	0.859	0.578	0.909	0.940	0.382	0.384	0.931	-0.303	0.937	1.000	
PanD	0.408	0.552	0.483	-0.192	0.485	0.159	0.515	0.494	-0.613	0.910	0.367	-0.253	0.567	0.365	1.000

	FTA	***STRIN***
FTA	1	
STRIN	-0.948	1

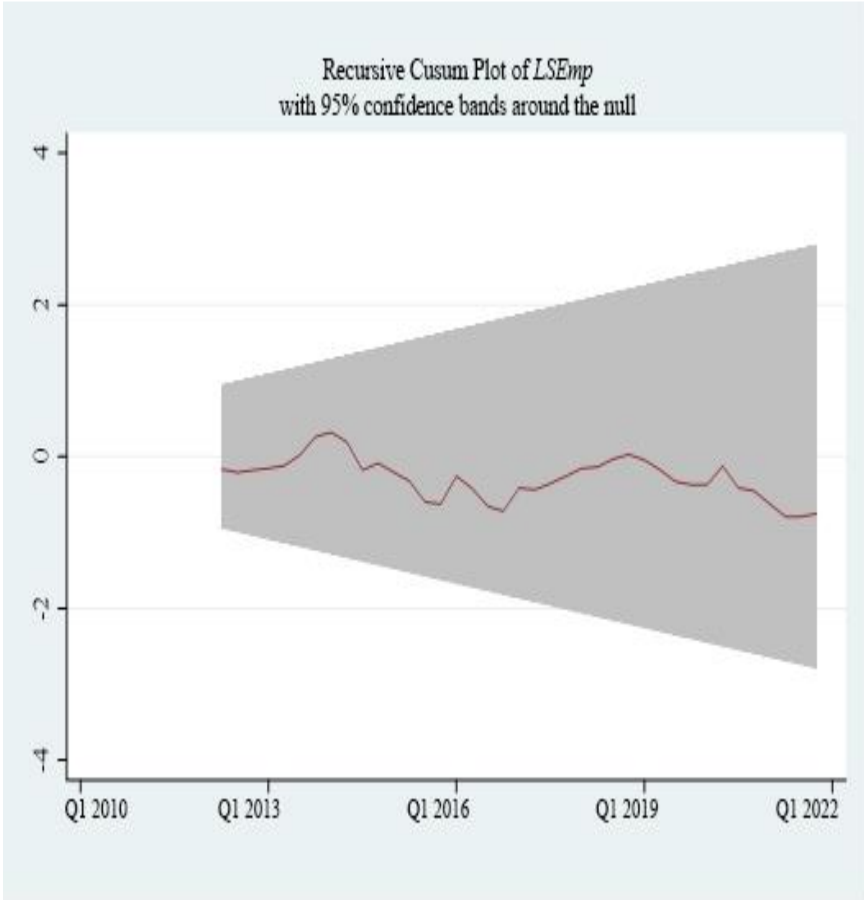
Source: Authors.

Figure 3: CUSUM Plot of Total Employment



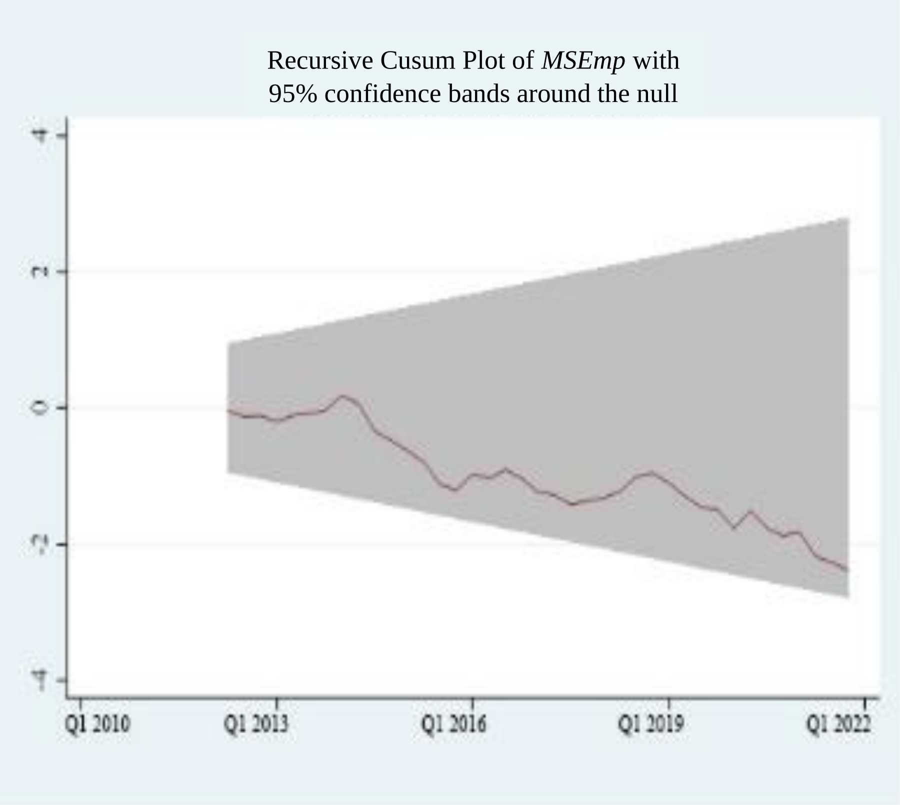
CUSUM = cumulative sum, Q = quarter.
Source: Authors.

Figure 4: CUSUM Plot of Low-skilled Employment



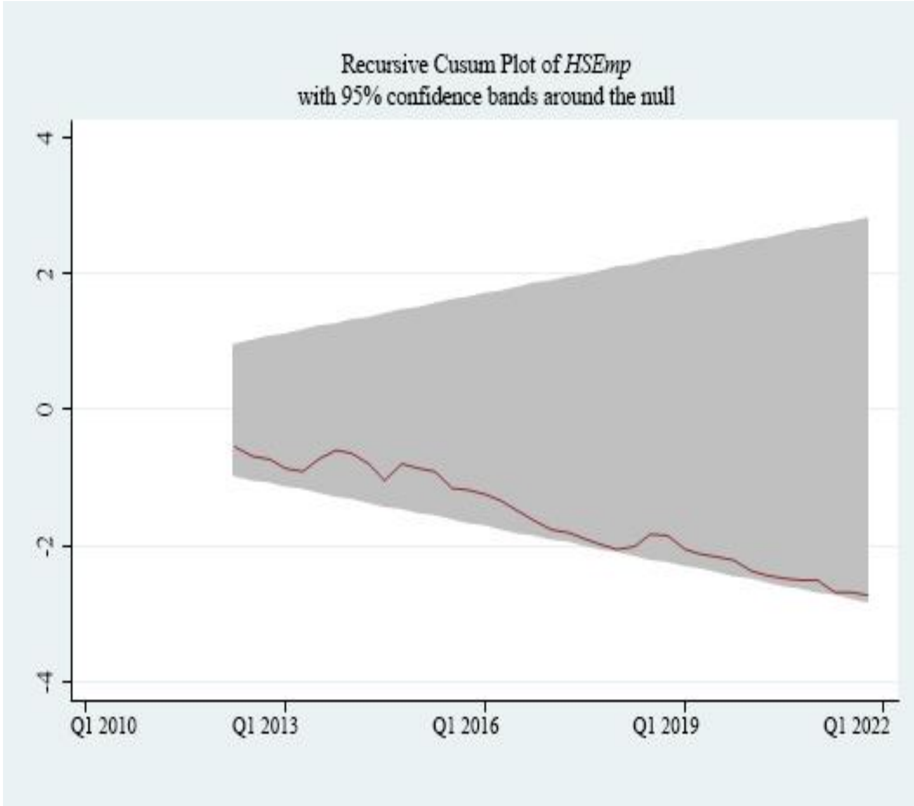
CUSUM = cumulative sum, Q = quarter.
Source: Authors.

Figure 5: CUSUM Plot of Medium-skilled Employment



CUSUM = cumulative sum, Q = quarter.
Source: Authors.

Figure 6: CUSUM Plot of High-skilled Employment



CUSUM = cumulative sum, Q = quarter.
Source: Authors.

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