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# The Covid-19 pandemic and European trade flows: Evidence from a dynamic panel model

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**Abstract**

This paper investigates the impact of the Covid-19 pandemic on trade flows in the case of the European countries. First, an ARDL dynamic panel model is estimated using the PMG method to analyse monthly data covering the most recent period (2019M1–2021M12); then, the GMM and PCSE approaches are applied to a much longer span of quarterly data (2000Q1–2021Q4), which also includes the Global Financial Crisis (GFC) of 2007–2009, in order to compare the trade impact of two different crises. The findings based on the monthly data provide clear evidence of the significant negative effects of the Covid-19 pandemic on both exports and imports in both the short and the long run, and also suggest that digitalisation was instrumental in mitigating the impact of the crisis and speeding up the recovery. The quarterly analysis over a longer time period indicates that both the GFC and the Covid-19 pandemic had negative effects on trade but of a different magnitude. The use of digital technology enabling remote work and e-commerce are again some of the factors likely explaining why international trade fell by less and also rebounded much more quickly during the Covid-19 pandemic compared to the GFC.

**KEYWORDS**

Covid-19 pandemic, digitalisation, dynamic panel models, global financial crisis, pooled mean group (PMG) estimator, trade flows

## 1 | INTRODUCTION

The Covid-19 pandemic has represented a massive shock for the global economy leading to a severe contraction in both output and trade. The initial expectation (WTO, 2020) was that the decline in trade would exceed that caused by the Global Financial Crisis (GFC) of 2007–2009 which had led to a 12% collapse in world trade. At that time banks experienced severe liquidity and solvency problems and national governments had to adopt policy measures to tackle them. By contrast, in the case of the current health crisis the impact on the economy has been caused mainly by restrictions on movement and social distancing affecting labour supply, transport and travel as never before, which has required measures to provide temporary income support to businesses and households. It is noteworthy that the restrictions have had an impact on trade of services rather than goods trade because the former, though dominant in the developed economies, account for only a quarter of global trade; as a result, world trade actually fell by 8.9%, namely by less than during the GFC and then initially forecast; further, the effects of the Covid-19 shock on trade differed across countries, China showing more resilience and reopening its domestic supply chains more rapidly (Bank of England, 2021). Initially there were both a supply shock leading to a fall in exports and a demand shock resulting in a decline in imports (Baldwin & Tomiura, 2020), but during 2021 trade recovered sharply and was expected to have returned to its pre-pandemic levels by the first quarter of 2022, though specific sectors and supply chains as well as regions that have been more heavily affected might take longer to recover (OECD, 2022).

The present paper aims to provide new evidence on the impact of the Covid-19 pandemic on trade flows (imports and exports) in the European countries. It makes a threefold contribution to the literature. First, it has a Europe-wide focus, unlike most previous studies which consider individual countries (e.g., Buchel et al., 2020; De Lucio et al., 2020) or a wide range of economies from different geographical areas (e.g., Barbero et al., 2021; Hayakawa & Mukunoki, 2021b). Second, the chosen empirical framework can capture both short- and long-run effects, again in contrast to most existing studies which do not distinguish between the two (e.g., Espitia et al., 2021; Khorana et al., 2021). More specifically, we estimate a dynamic panel data model following the ARDL (AutoRegressive Distributed Lag) approach and using the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (1999), which restricts the long-run slope coefficients to be the same across countries but allows the short-run ones and the regression intercept to be country-specific. This method yields consistent estimates of the coefficients despite the possible presence of endogeneity because it includes lags of both the dependent and independent variables, and captures both short- and long-run effects (Pesaran et al., 1999). Third, in addition to monthly data covering the pandemic period, we also use quarterly series to carry out the analysis over a much longer sample period going from 2000 to 2021, which enables us to include shift dummies for both the 2007–2009 GFC and the Covid-19 pandemic and compare their effects on trade, thus investigating further the issue of trade resilience during the latter crisis.[1] Our findings can provide guidance to policy-makers on appropriate trade policies during a crisis such as the Covid-19 pandemic when international policy coordination can lead to a faster recovery (WTO, 2020). They are also relevant for market participants having to choose appropriate trade strategies.

The layout of the paper is the following: Section 2 briefly reviews the relevant literature; Section 3 outlines the methodology; Section 4 describes the data; Section 5 presents the empirical results; Section 6 offers some concluding remarks.

## 2 | LITERATURE REVIEW

The literature on the impact of the Covid-19 pandemic on trade is a recent one but it is rapidly growing. The first academic studies analysing the economic effects of the pandemic in most cases used global computable general equilibrium models (Baldwin & Tomiura, 2020; Maliszewska et al., 2020; McKibbin & Fernando, 2020; OECD, 2020; Orlik et al., 2020; WTO, 2020). Some subsequent papers looked at individual countries such as Kenya (Socrates, 2020), Switzerland and Spain, in the latter two cases the Covid-19 containment measures being found to lead to sharp falls in trade (Buchel et al., 2020; De Lucio et al., 2020 and Minondo, 2021); concerning China, Che et al. (2020) analysed total export flows, whilst Fuchs et al. (2020) and Telias and Urdinez (2020) reported a fall in the exports of medical goods, and Friedt and Zhang (2020) in the supply of machinery parts; finally, Meier and Pinto (2020) found that US industries with a large exposure to intermediate goods imports from China experienced a sharp fall in both exports and imports.

Other studies have instead considered a wider set of countries and analysed the effects of the Covid-19 pandemic on international trade through the transmission of demand and supply shocks or through supply chains. For instance, Kejzar and Velic (2020) estimated a gravity model using monthly bilateral trade data for EU member states over the period from June 2015 to May 2020 and found that supply chains disruptions played a significant role in the transmission of Covid-19 demand shocks. Espitia et al. (2021) examined a sample of 28 countries and concluded that the pandemic affected sectoral trade growth negatively by decreasing countries' participation in Global Value Chains (GVCs). Hayakawa and Kohei (2021) focused on trade in medical goods and reported that Covid-19 restrictions lowered exports of medical products in a large sample of countries. Hayakawa and Mukunoki (2021a) investigated the effects of lockdown orders on trade using worldwide trade data, whereas Hayakawa and Mukunoki (2021b) looked at exports of finished machinery products. Verschuur et al. (2021) analysed maritime trade shipping data for various countries and found a sharp decline in trade. Khorana et al. (2021) focused on the Commonwealth countries over the period from January 2019 to November 2020 and provided evidence that the Covid-19 pandemic had a negative impact on exports in the case of low-income countries and a positive one in high-income economies. Liu et al. (2022) found that lockdown restrictions affected monthly year-over-year growth of imports from China for all destinations to which China exported goods in 2019–2020 more than the direct effects of the pandemic.

More sophisticated econometric methods, specifically dynamic panel data models, have been used in some very recent studies. In particular, Caporale et al. (2021) applied the system Generalized Method of Moments (GMM) approach to exports and imports data for 35 OECD countries over the period 2019Q1-2021Q2; they found that the negative effects of the Covid-19 pandemic on international trade can be attenuated through (policies supporting) private credit, which confirms the importance of the trade-finance nexus. Barbero et al. (2021) estimated a gravity model applying the Poisson pseudo maximum likelihood (PPML) estimator to monthly trade data for 68 countries exporting across 222 destinations between January 2019 and October 2020; this method removes heteroscedasticity by taking logarithms of trade flows, allows the inclusion of zeros in the regression, and can also capture multilateral resistance terms (MRTs) reflecting the impact of third countries on bilateral relationships (Head & Mayer, 2014); their main findings are that there was a greater negative impact of Covid-19 on bilateral trade for countries belonging to regional trade organisations before the pandemic, and that the strongest negative effects of the Covid-19 containment measures occurred in the case of exports between high-income countries. Hayakawa and Mukunoki (2021b) also used the PPML estimator to examine monthly exports of 34 countries to 173 countries from January to August in 2019 and 2020 in the context of a gravity equation and using four different Covid-19 proxies; they found that the negative effects of the pandemic on the international trade flows of both exporting and importing countries tended to become insignificant after July 2020 and were heterogeneous across industries.

As already mentioned, unlike the studies reviewed above, the present one focuses on Europe; in addition, it adopts a dynamic panel data approach which sheds light on both short- and long-run effects, and it considers a much longer data span, which enables us to compare the impact on trade of the GFC and of the current pandemic respectively.

## 3 | METHODOLOGY

The empirical framework is based on the ARDL (autoregressive distributed lag) approach originally introduced by Pesaran and Shin (1999) in a time series context, which is also suitable for variables exhibiting different orders of integration. Pesaran et al. (1999) extended it to the case of heterogenous panels; consistent estimates of both the short- and long-run coefficients are obtained by including lags of both the dependent and independent variables, thereby solving the endogeneity problem.

Specifically, Pesaran et al. (1999) consider a dynamic heterogeneous panel regression model with the following autoregressive distributed lag ARDL (p,q,...q) specification:

$$\Delta(Y_i)_t = \sum_{j=1}^{p-1} \gamma_j^i \Delta(Y_i)_{t-1} + \sum\nolimits_{j=0}^{q-1} \delta_j^i \Delta(X_j)_{t-1} + \varphi^i\left[(Y_i)_{t-1} - \left\{\beta_0^i + \beta_1^i (X_i)_{t-1}\right\}\right] + \mu_I + \varepsilon_{it} \quad (1)$$

Where $Y_i$ is the independent variable, $X_j$ is a set of explanatory variables, $\Delta$ is the difference operator, $\gamma$ and $\delta$ represent the short-run coefficients of the lagged dependent and explanatory variables respectively, $\beta^i$ are the long-run coefficients, $\varphi$ is the error-correction coefficient measuring the speed of adjustment to the long-run equilibrium, $\mu_{\text{i}}$ are individual effects and $\varepsilon_{it}$ are the error terms. The subscripts $i$ and $t$ represent country and time, respectively. The expression in square brackets is the long-run equilibrium relationship.

Equation (1) can be estimated using three different estimators: the Pooled Mean Group (PMG) one developed by Pesaran et al. (1999), the Mean Group (MG) one of Pesaran and Smith (1995), and the Dynamic Fixed Effects (DFE) one (see Nickell, 1981, for some of the issues arising in this context). All three estimators are computed by maximum likelihood. Their key features are discussed in greater detail in Appendix A. For our purposes we use the PMG estimator which is preferable to the MG and DFE ones for the reasons explained by Pesaran et al. (1999). In particular, it allows for heterogeneity in the short-run dynamics whilst assuming long-run homogeneity and can be used instead of estimating separate regressions (which allows the coefficients and error variances to differ across the groups) and applying conventional fixed-effects estimators (which assumes the same slope coefficients and error variances in all cases).[2]

The ARDL specification used here for analysing the response of trade to the Covid-19 pandemic is the following:

$$\Delta \mathrm{TRD}_{i,t}^{s} = \sum\nolimits_{l=0}^{p-1} \gamma_{i,l} \Delta \mathrm{TRD}_{i,t-l}^{s} + \sum\nolimits_{l=0}^{q-1}\left(\tau_{i,k}\Delta \mathrm{COVID}_{i,t-l}^{k} + \sum\nolimits_{j=1}^{J} \rho_{i,j}\Delta X_{i,t-l}^{j}\right) + \varphi_i\left[\mathrm{TRD}_{i,t-1}^{s} - \left\{\beta_{i,0} + \varrho_{i,k}\mathrm{COVID}_{i,t-1}^{k} + \sum\nolimits_{j=1}^{J}\beta_{ij}X_{i,t-1}^{j}\right\}\right] + \mu_i + \varepsilon_{i,t} \quad (2)$$

Where: $\mathrm{TRD}_{i,t}^{s}$ = international trade ($s$ = 1...3–exports, imports, total trade), $\mathrm{COVID}^{\mathrm{k}}$ ($k$ = 1,2) can stand for either STR = Stringency index or GOV-RESP = Government response index, $X^{\mathrm{j}}$ = Control variables ($j$ = 1...4), RGDPC = real income per capita, INFL = Consumer Price Index, WUI = World Uncertainty Index, and DESI = Digital Economy and Society Index; $\gamma$, $\tau$ and $\rho$ are the short-run coefficients on the lagged dependent and independent variables; $\varrho$ and $\beta_i$ are the long-run coefficients,

$\varphi_i$ is the coefficient measuring the speed of adjustment to the long-run equilibrium, and $\mu_i$ stands for the fixed effects. The subscripts $i$ and $t$ denote country and time, respectively, and $l$ is the lag length. The term in square brackets represents the long-run equilibrium. The error term $\varepsilon_{i,t}$ is assumed to be independently distributed across $i$ and $t$, but the variances are allowed to be heterogeneous across countries.

More precisely, we estimate Equations (3)–(5) below to examine the effects of the Covid-19 pandemic on exports, imports and total trade respectively in both the short and the long run:

$$\begin{aligned}\Delta \mathrm{EXP}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{EXP}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{EXP}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned}\Delta \mathrm{IMP}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{IMP}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{IMP}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

$$\begin{aligned}\Delta \mathrm{TRADE}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{TRADE}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{TRADE}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

During the pandemic period, governments were forced to adopt lockdown and social distancing measures to contain the spread of the virus and protect public health. Those had a severe impact on trade and the economy as a whole. However, in the case of sectors characterised by digitalization, which facilitates remote work arrangements and e-commerce through the use of information and communication technology, the negative effects of reduced worker mobility on production and trade were less pronounced. To capture the role of digitalization and technology in the both the short and the long run an interaction variable (DESI $\times$ COVID$^{k}$) is added to the model which then takes the following form:

$$\begin{aligned}\Delta \mathrm{EXP}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{EXP}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \\ & + \rho_{i,5} \Delta \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{EXP}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \\ & + \beta_{i,5} \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned}\Delta \mathrm{IMP}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{IMP}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \\ & + \rho_{i,5} \Delta \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{IMP}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \\ & + \beta_{i,5} \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{7}$$

$$\begin{aligned}\Delta \mathrm{TRADE}_{i,t} = {} & \sum_{l=1}^{p-1} \gamma_{i,l} \Delta \mathrm{TRADE}_{i,t-1} + \sum_{l=0}^{q-1} \Big( \tau_i \Delta \mathrm{COVID}^{k}_{i,t-1} \\ & + \rho_{i,1} \Delta \mathrm{RGDPC}_{i,t-l} + \rho_{i,2} \Delta \mathrm{INFL}_{i,t-l} \\ & + \rho_{i,3} \Delta \mathrm{WUI}_{i,t-l} + \rho_{i,4} \Delta \mathrm{DESI}_{i,t-l} \\ & + \rho_{i,5} \Delta \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-l} \Big) \\ & + \varphi_i \Big[ \mathrm{TRADE}_{i,t-1} - \Big\{ \beta_{i,0} + \varrho_{i,1} \mathrm{COVID}^{k}_{i,t-1} \\ & + \beta_{i,1} \mathrm{RGDPC}_{i,t-1} + \beta_{i,2} \mathrm{INFL}_{i,t-1} \\ & + \beta_{i,3} \mathrm{WUI}_{i,t-1} + \beta_{i,4} \mathrm{DESI}_{i,t-1} \\ & + \beta_{i,5} \mathrm{COVID}^{k}_{i,t-1} \times \mathrm{DESI}_{i,t-1} \Big\} \Big] + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Note that within this framework consistent and efficient estimates can be obtained of the long-run cointegration parameters in square brackets. Before proceeding to the estimation, panel unit root tests are carried out as in Levine et al. (LLC, Levine et al., 2002), Harris and Tzavalis (1999) and Breitung (2000). The main difference between these methods is that the first two are based on the assumption of a common panel unit root with identical autocorrelation coefficients, whilst the third one eliminates the potential problem of cross-sectional dependence by subtracting the cross-sectional means. The test results suggest that all the series used for the analysis are stationary in first differences.[3]

The above models are estimated using monthly data for the period 2019M1–2021M12. Next, in order to be able to compare the effects on trade of the Covid-19 pandemic to those of the GFC of 2007–2009, we analyse quarterly data for the period from 2000Q1 to 2021Q4 and include in the model shift dummies for both crises. Specifically, we use in turn the Generalized Method of Moments (xtabond2) and linear regressions with Panel-Corrected Standard Errors (PCSE). Both these methods have considerable advantages over alternative ones. Specifically, the GMM approach assumes that the first differences of the instrumental variables are not correlated with the fixed effects and thus allows using more instruments, which improves efficiency.[4] As for the PCSE estimator, it has the advantage of allowing for heterogeneity and contemporaneous correlation.[5] Implementing these methods we estimate a dynamic model of the following type:

$$Y_{i,t} = \alpha_i Y_{i,t-1} + \sum_{k=1}^{K} \beta_i^k X_{it}^k + \mu_i + \eta_t + \varepsilon_{i,t} \tag{9}$$

Where: $i$ = 1…N are the individual countries, $t$ = 1…T stands for time, $k$ = 1…K – are the explanatory variables, $\mu_{\mathrm{i}}$ are the individual effects, $\eta_{\mathrm{t}}$ are the time effects and $\varepsilon_{\mathrm{it}}$ is the error term that can be autocorrelated over $t$ or contemporaneously correlated across $i$.

In our case, the dynamic model including the two crisis periods is specified as follows:

$$\begin{aligned}\mathrm{TRD}_{i,t}^{s} = {} & \alpha_i \mathrm{TRD}_{i,t-1}^{s} + \beta_{i,1}\mathrm{RGDPC}_{i,t} + \beta_{i,2}\mathrm{STAB}_{i,t} \\ & + \beta_{i,3}\mathrm{EF\_GOV}_{i,t} + \beta_{i,4}\mathrm{COR}_{i,t} + \beta_{i,5}\mathrm{FCRISIS}_{i,t} \\ & + \beta_{i,6}\mathrm{DCOVID}_{i,t} + \mu_t + \eta_i + \varepsilon_{i,t}\end{aligned} \tag{10}$$

Where: $\mathrm{TRD^s}$ = international trade ($s$ = 1…3 – exports, imports, total trade), RGDPC = real income per capita, STAB = Political Stability and Absence of Violence/Terrorism, EF-GOV = Government Effectiveness, COR = Control of Corruption, FCRISIS = a financial crisis dummy which is equal to 1 during the GFC of 2007–2009 and zero elsewhere, DCOVID = a Covid-19 pandemic dummy which is equal to 1 during 2020–2021and zero elsewhere.

## 4 | DATA DESCRIPTION

To analyse the impact of the Covid-19 pandemic on trade, we use a set of variables which have been selected on the basis of the theoretical and empirical literature discussed in Section 2.[6] They are the following:

TRADE, EXP and IMP, which are indicators for trade, exports and imports respectively (source: UN COMTRADE database);

$\mathrm{COVID^k}$, which measures the impact of the pandemic through the restrictions imposed by national governments and is the main variable of interest. More precisely, for robustness purposes we use two alternative indicators, namely the stringency (STR) and the overall government response index (GOV- RESP). The former is a narrow index which is based on 9 indicators of restrictive measures (e.g., school closures, workplace closures, and travel bans), whilst the latter includes a wider set of containment and closure policies, health system policies and economic policies. Their evolution during the pandemic can be seen in Figure A1 in Appendix B. Stringency increased in the first two quarters of 2020 and started to decrease in the third quarter of 2021 when governments lifted some of the restrictions. The overall government response also increased in the first quarter of 2020 and since then has remained at a relatively stable level. These data are taken from the Oxford Covid-19 Government Response Tracker (OXCGRT) [3].

Four control variables are included in the estimated models, namely:

1. Real GDP per capita (RGDPC) (with an expected positive effect on trade) – these series are taken data from the OECD and EUROSTAT databases.
2. World Uncertainty Index (WUI): this is a new measure that tracks uncertainty across the globe by text mining the country reports of the Economist Intelligence Unit (with an expected negative effect on trade) – this series has been obtained from https://www.worlduncertainty.com. As pointed out by Ahir et al. (2022), this index has a key advantage relative to alternative uncertainty measures, namely it is more easily comparable across countries because it is based on a single source focusing on economic and political developments and it adopts a standardised approach

resulting in comparable values. On the whole, it is more consistent and accurate than other measures.

3. The consumer price index (INFL) (with an expected negative effect on exports and a positive one on imports) – the source is the EUROSTAT database;
4. DESI = Digital Economy and Society (DESI) index: this is a composite index published by the European Commission ranging from 0 to 100, with higher values corresponding to higher levels of technological development (and has an expected positive impact on trade). More precisely, it measures the progress made in European countries in digital competitiveness in areas such as human capital, broadband connectivity, the integration of digital technologies by businesses and digital public services. Its highest values in 2021 are for Denmark (70), Finland (67.1) and Sweden (66.1), and the lowest ones for Greece (37.3) and Bulgaria (36.8). Figure A2 in Appendix B displays this index for the individual European states.
5. To capture the role of digitalization in mitigating the adverse effect of the Covid-19 pandemic on trade we add to the benchmark model an interaction term, DESI × COVID, where COVID stands in turn each of the two pandemic indices used for the analysis, such that the additional regressor is defined in turn as DESI x STR and DESI x GOV_RES (see Equations 5 and 6 respectively).

All the above series are monthly, cover the period 2019M1–2021M12, and have been obtained for 31 European countries.[7]

In the second part of the analysis, which aims to compare the impact on trade of the GFC and of the Covid-19 pandemic respectively, we extend the sample and we use quarterly data over the period 2000Q1–2021Q4 for a larger set of 40 European countries.[8] Also, we add to the model three series taken from the Worldwide Governance Indicators (WGI),[9] namely Political Stability (STAB), Governance Effectiveness (EF-GOV) and Corruption Control (COR), which are defined as follows (see www.govindicators.org):

1. "Political Stability measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism."
2. "Government Effectiveness reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies."
3. "Control of Corruption reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests."

These indicators range between −2.5 to 2.5 (weak to strong Political Stability Government Effectiveness or Control of Corruption) (see Figure A3 in Appendix B).

# 5 | EMPIRICAL RESULTS

## 5.1 | Monthly estimates for the Covid-19 pandemic period

Tables A1–A3 in Appendix C report the PMG estimates of the short and long-run effects of the Covid-19 pandemic on exports, imports and total trade for the shorter sample period with monthly data. First, we analyse the direct effects on trade of each of the two Covid-19 pandemic indices; second, we also include DESI, and finally we add an interaction term (i.e., DESI × $COVID^k$) as well.

In the case of exports (Table A1), the Stringency Index is found to have had a negative short-run effect, which confirms that restrictions such as social distancing, workplace and border closures, and travel bans had an adverse impact as one would have expected. Export volumes of the European countries in fact decreased by 28% during the first two quarters of 2020 (see Figure A5 in Appendix B), mainly as a result of reduced mobility of workers and higher transport costs. Similar results are obtained when including the wider government response index. The key role of digitalization in mitigating the impact of the pandemic is confirmed by the estimates displayed in columns 3 and 6. In particular, the positive coefficient on the interaction term implies a smaller effect of the restriction measures in the presence of a higher level of digitalization. Even though export volumes decreased considerably in the European countries during the first two quarters of 2020, they were already back to their pre-crisis level by the end of the third quarter of 2020 (see Figure A4 in Appendix B). Clearly digitalization played an essential role during the pandemic by allowing work to be done remotely in the presence of lockdown restrictions, thereby increasing resilience. The long-run effects on exports of both the stringency and overall government index are also found to be negative, and it is again clear that the digitalization of more companies and of the public administration, the enhancement of digital skills and the deployment of high capacity networks have a positive impact and are key factors for economic recovery.

Concerning imports (Table A2), the estimated coefficients for both indices again imply that lockdown policies had an adverse short-run and long-run effect by restricting movement as well as increasing unemployment and lowering income (and thus demand). As in the case of exports, digitalization is found to mitigate the impact of the pandemic. As for total trade (Table A3), the estimates again suggest that lockdown policies had a negative impact both in the short and in the long run, and as before digitalization is found to have mitigated the impact of the pandemic on trade flows.

Finally, regarding the control variables, the coefficients are mostly significant and have the expected sign in all the equations (Tables A1–A3): real GPD per capita has a positive and significant impact and uncertainty a negative one, whilst inflation has a negative effect on exports and a positive one on imports.

On the whole, our analysis using monthly data provides evidence of the detrimental effects on trade of the Covid-19 pandemic and of the restrictions imposed by national governments. However, it also points to a remarkable degree of resilience of the European economies, as already found by Le Moigne and Ossa (2021). A possible explanation for this finding is the role played by digitalization and policies to promote it, which have reduced the adverse impact of the pandemic and boosted trade both in the short and in the long run. This is clearly shown by the positive and significant coefficient on the interaction term, which implies that digitalization has reduced the impact of the Covid-19 pandemic for the panel as a whole; this mitigating effect has presumably been greater in the case of countries with a higher level of digitalization such as Denmark, Finland and the Netherlands (see Figure A2 in Appendix B).[10]

### 5.2 | Quarterly estimates for the longer sample including the Global Financial Crisis of 2007–2009

Prior to the Covid-19 pandemic the most recent crisis severely hitting the world economy was the GFC of 2007–2009. Trade collapsed in both cases, but the causes were different. During the GFC liquidity and solvency problems in the banking sector were the main factors leading to lower trade, with exports decreasing by 14.4% in 2009 in the case of the European countries and manufacturing products being the most affected by the GFC.[11] By contrast, banks entered the current health crisis with a higher level of capital and liquidity, and cost and capital relief measures have been adopted to support bank lending during the pandemic (see Altavilla et al., 2020), with credit to the private non-financial sector increasing in most OECD countries during this period. Caporale et al. (2021) have shown the importance of the trade-finance nexus in the context of the current pandemic, and also of policies aimed at encouraging lending and boosting liquidity, which could be more effective than fiscal packages in helping the economy to recover. Consequently, as already mentioned, in the case of the Covid-19 pandemic the key factors bringing about a collapse in trade were of a different nature, namely the restrictive measures affecting mobility and leading to lower income and demand. It is therefore interesting to compare the behaviour of trade during those two crises.

The GMM and PCSE estimates of the quarterly model we use for this purpose are reported in Tables A4 and A5 respectively. For each of the dependent variables (total trade, exports and imports), we estimate three different specifications, including in turn the GFC dummy, the Covid-19 dummy, and both. Sub-sample estimates are then also reported for the periods 2000Q1-2010Q4 and 2011Q1-2021Q4.

The results are very similar, whichever estimation method is used. In particular, both dummy coefficients are negative and significant for trade as a whole and also for exports and imports. Although the GFC had a greater impact and was followed by a longer recovery period (see Figure A6 in Appendix B), the recent pandemic also had an adverse effect on all major determinants of global trade: the supply of traded goods was disrupted by lockdowns and plants closures; demand for traded goods decreased owing to higher income uncertainty and higher unemployment in addition to social distancing measures; trade costs increased as a result of export restrictions and closed borders. However, trade seems to have been more resilient compared to 2007–2009: initial concerns did not materialise, and by mid-2020 trade volumes had recovered to pre-pandemic levels. As previously pointed out, this is likely to reflect the increasing importance of digitalization, which has reduced the impact of the pandemic, as well as the measures adopted by national governments to support business and households. Regarding the control variables, as expected we find a positive effect of income, whilst corruption control, government efficiency, and political stability appear to have had instead a negative impact in all cases.

## 6 | CONCLUSIONS

This paper has investigated the impact of the Covid-19 pandemic on trade flows in the case of the European countries. First, an ARDL dynamic panel model has been estimated using the PMG method to analyse monthly data covering the most recent period (2019M1–2021M12);

then, the GMM and PCSE approaches have been applied to a much longer span of quarterly data (2000Q1–2021Q4) including the GFC as well in order to compare the trade impact of two different crises.

Our findings based on the monthly data provide clear evidence of the significant negative effects of the Covid-19 pandemic on both exports and imports and trade as a whole, with countries decreasing their participation in Global Value Chains. In particular, exporting countries experienced a reduction in production and in export supply reflecting higher transport and labour costs, whilst imports fell as a result of lower demand driven by lower income, higher unemployment and restrictions on social mobility. Governments adopted various measures to reduce the effects of the pandemic; these included income and credit support, debt relief and policies promoting digitalization. Our analysis suggests that the latter was instrumental in increasing trade resilience and helping the economy to recover, both in the short and in the long run. In particular, it made remote work possible in a number of sectors which were then less affected by the lockdown restrictions and recovered more quickly. Further, it led to an increase in e-commerce, which also mitigated the impact of the pandemic on trade as a whole (see Figure A7 in Appendix B). Overall it is clear that digitalization increased trade resilience, both in the short and in the long run, and thus appropriate policies to promote it should be adopted to reduce the impact of future shocks.

The quarterly analysis over a longer data span indicates that both the GFC and the Covid-19 pandemic had negative effects on trade but of a different magnitude. This is not surprising given the fact that the two crises had different causes, which also required different policy responses. Specifically, the main issue in the case of the GFC was lack of liquidity, whilst in the case of the Covid-19 pandemic the economy was mainly hit by the restrictive measures adopted by governments to contain the spread of the virus. In fact during this period credit increased and was one of the factors behind trade resilience (Caporale et al., 2021). As already mentioned, the use of digital technology enabling remote work and e-commerce were additional factors explaining why international trade fell by less and also rebounded much more quickly during the Covid-19 pandemic compared to the GFC (as already found by Le Moigne & Ossa, 2021) – more precisely it had already returned to its previous levels by the third quarter of 2020, whilst it had taken more than 2 years to recover to its pre-crisis levels during the GFC (see Figure A6 in Appendix B). On the whole, our analysis shows the importance of digitalization to make economies less vulnerable to exogenous shocks, which has important implications for both policy-makers aiming to promote growth and businesses seeking to maximise profits. Further, the Covid-19 pandemic generated much higher economic uncertainty and also shifts in consumer spending patterns. Policy makers can learn a number of lessons from this experience to design more effective mitigation strategies and policy responses to deal with future pandemics. In particular, one key issue is trade policy cooperation, which is essential to preserve open markets, especially during a crisis, export restrictions and import protection being inefficient (Rocha et al., 2020).

## ACKNOWLEDGEMENTS

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## ENDNOTES

[1] Le Moigne and Ossa (2021) found that world trade displayed much greater resilience in 2020 than during the GFC.

[2] The same method has been used to analyse trade flows in the case of the CEEC-6 and the trade-finance nexus in a wider set of European countries by Caporale et al. (2022a and 2022b) respectively.

[3] The test results are not reported to save space but are available upon request.

[4] See Caporale et al. (2022c) for a previous application of this method to trade data to analyse the case of European exports and imports at the sectoral and product level.

[5] See Appendix A for more details on these methods.

[6] Please note that, with the exception of the variables specifically measuring the impact of the pandemic on trade (which is our main focus), those for uncertainty, inflation or GDP are also used in many other trade studies (e.g., Novy & Taylor, 2020; Stockman, 1985).

[7] They are the following ones: Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Croatia, Denmark, Estonia, Finland, France, Greece, Germany, Hungary, Ireland, Iceland, Italy, Luxembourg, Latvia, Lithuania, Malta, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Switzerland, Sweden, Spain, United Kingdom.

[8] They include the following ones: Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Cyprus, Czech Republic, Croatia,

Denmark, Estonia, Finland, France, Greece, Germany, Hungary, Ireland, Iceland, Italy, Latvia, Luxembourg, Lithuania, Macedonia, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Switzerland, Sweden, Spain, Ukraine, United Kingdom.

[9] The WGI dataset summarises the views on the quality of governance gathered from a number of survey institutes, think tanks, non-governmental organisations, international organisations, and private sector firms.

[10] As a robustness check, we also carried out the estimation of the monthly model using the MG and DEF estimators instead of the PMG one. The results (not reported for reasons of space, but available upon request) were very similar.

[11] In particular, exports of industrial machinery and vehicles decreased by 29% and 32% respectively in 2009.

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# APPENDIX A

## A.1 | Estimators for the ARDL models

*Pooled mean group* (*PMG*) *estimator* – Its main characteristic is that it restricts the long-run slope coefficients to be homogeneous across units, whilst the short-run ones, including the intercepts, the speed of adjustment to the long-run equilibrium, and the error variances are allowed to be heterogeneous. The following conditions have to be met:

1. the existence of a long-run relationship amongst the variables of interest requires the coefficient on the error–correction term to be negative and not lower than $-2$ (a positive value indicates divergence, and a negative one convergence towards equilibrium);
2. for the consistency of the ARDL model the residuals of the error-correction model should be serially uncorrelated;
3. a large T (time) and N (units) avoid bias in the average estimators and solve the problem of heterogeneity.

*Mean group* (*MG*) *estimator* – This method estimates separate regressions for each unit and calculates the coefficients as unweighted means of the estimated coefficients for the individual units. It allows for all coefficients to vary and be heterogeneous in both the long and the short run. A necessary condition for the consistency of this approach is to have a sufficiently large time-series dimension of the data.

*Dynamic fixed effects* (*DFE*) *estimator* – This approach is very similar to the PMG one in that it restricts the slope coefficient and error variances to be equal across all units in the long run, and also imposes equality of the speed of adjustment and the short-run coefficients. The Hausman test can be used to establish whether there are significant differences between the estimates obtained using these three different methods.

## A.2 | Generalized method of moments (GMM) method

The Arellano and Bond (1991) and Arellano and Bover (1995)/Blundell and Bond (1998) dynamic panel estimators are general ones designed for panels with many units and few periods, a linear functional relationship, a single dependent variable which is dynamic, independent variables which are not strictly exogenous, fixed individual effects, heteroscedasticity and autocorrelation within individuals but not between them. The Arellano and Bond (1991) estimation starts with transforming all regressors, usually by taking differences, and then uses the generalized method of moments (Hansen, 1982), and is therefore called Difference GMM. By making the assumption that "the first differences of the instrumental variables are not correlated with the fixed effects" the Arellano–Bover/Blundell–Bond estimator allows introducing more instruments, thereby considerably improving efficiency. It constructs a system of two equations (the original equation as well as the transformed equation), which is known as the GMM System. The xtabond2 programme (proposed by Roodman, 2009) implements these estimators making a series of additions such as:

1. Windmeijer's (2005) finite sample correction to the standard errors reported in the two-step estimation, without which these standard errors tend to be heavily biased downwards;
2. automatic Sargan/Hansen difference tests for the validity of instrument subsets;
3. forward orthogonal gap transformation, which preserves sample size in panels with gaps;
4. appropriate autocorrelation test for linear GMM regressions on panels, especially important when lags are used as instruments.

The Sargan/Hansen test and autocorrelation (AR) test are reported automatically using xtabond2.

### A.3 | Panel-corrected standard errors (PCSE) method

Time-series cross-sectional data are likely to be characterised by complex error structures. Ordinary Least Squares (OLS) produces inefficient coefficient estimates and the corresponding standard error estimates are biased. By contrast, Generalized Least Squares (GLS) yields efficient estimates and unbiased standard errors, given certain assumptions such as: the error covariance structure is correctly specified, and the elements of the error covariance matrix are known. Feasible GLS(FGLS) is used when the structure of the error covariance matrix is known, but its elements are not. The finite sample properties of FGLS are analytically indeterminate.

Beck and Katz (1995) used Monte Carlo methods to study the performance of FGLS in a statistical environment characterised by (i) group-wise heteroscedasticity, (ii) first-order serial correlation, and (iii) contemporaneous cross-sectional correlation. They reported the following:

1. FGLS (Parks) produces inaccurate standard errors whilst the alternative estimator, based on OLS but using "panel-corrected standard errors" (PCSE), yields accurate ones.
2. The efficiency advantage of FGLS(Parks) over PCSE is at best slight, except in extreme cases of cross-sectional correlation, and then only when the number of time periods ($T$) is at least twice the number of cross-section units ($N$).

Panel-corrected standard errors, an alternative to feasible generalized least squares (FGLS), fits linear cross-sectional time-series models when the disturbances are not assumed to be independent and identically distributed (i.i.d.) but instead to be either heteroscedastic or heteroscedastic and contemporaneously correlated across panels. The disturbances can also be assumed to be autocorrelated within panel, and the autocorrelation parameter can be constant across panels or different for each panel.

## APPENDIX B

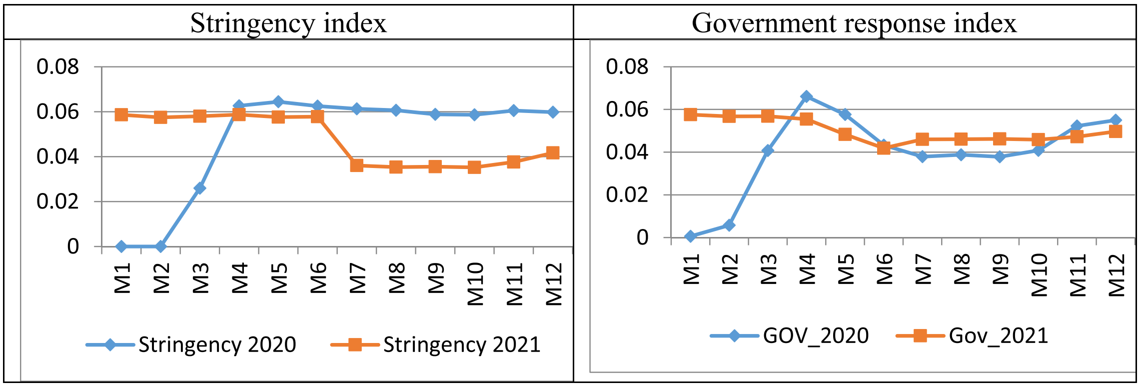


**FIGURE B1** Stringency and Government response indices during the Covid-19 pandemic period, 2020–2021. *Source*: Authors' calculations using data from the OXCGRT database [Colour figure can be viewed at wileyonlinelibrary.com]

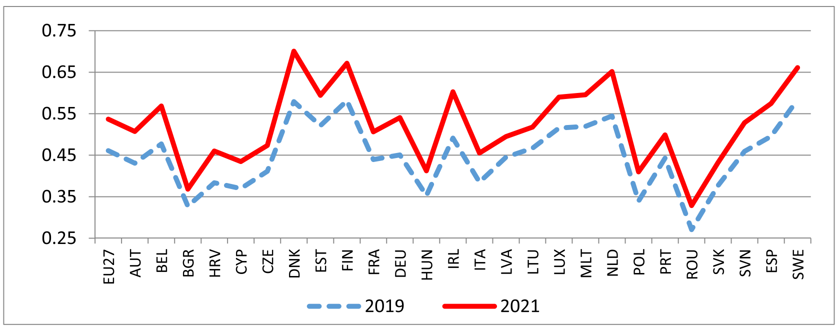


**FIGURE B2** Digital Economy and Society Index (DESI) for the European countries. *Source*: European Commission – https://digital-strategy.ec.europa.eu/en [Colour figure can be viewed at wileyonlinelibrary.com]

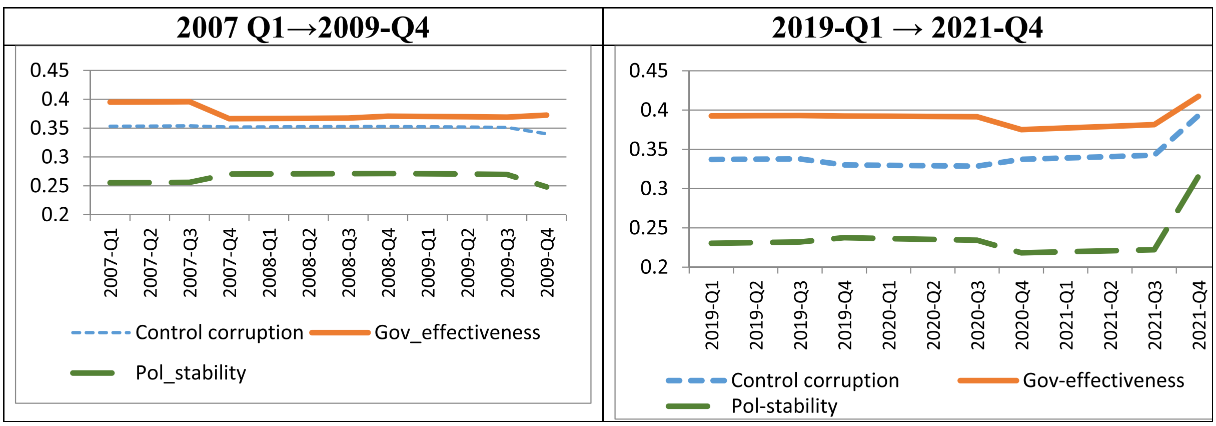


**FIGURE B3** Control of corruption, Government effectiveness and Political stability in the European countries during the Covid-19 pandemic and the Global Financial Crisis periods. *Source*: Worldwide Governance Indicators (WGI) [Colour figure can be viewed at wileyonlinelibrary.com]

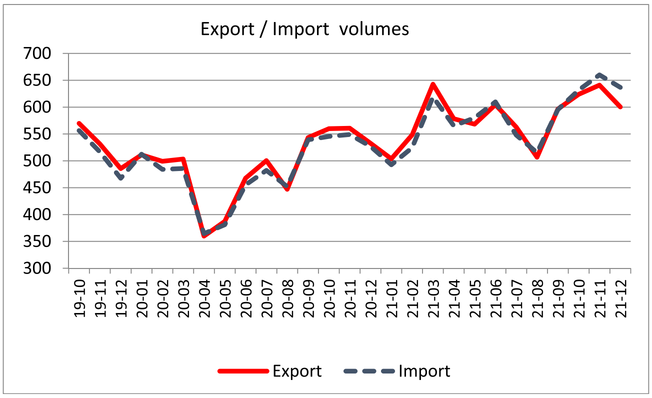


**FIGURE B4** Monthly European countries export/import volumes, 2019M10–2021M12. *Source*: Trade data from the UN COMTRADE database [Colour figure can be viewed at wileyonlinelibrary.com]

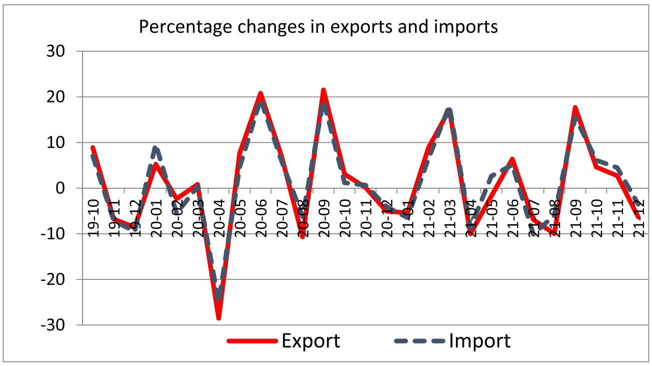


**FIGURE B5** Percentage changes in exports and imports in the European countries, 2019–2021. *Source*: Authors' calculations using trade data from the UN COMTRADE database [Colour figure can be viewed at wileyonlinelibrary.com]

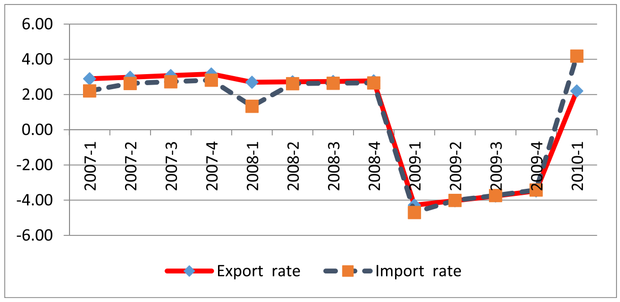


**FIGURE A6** The impact of the 2007–2009 Global Financial Crisis on exports and imports. *Source*: Authors' calculations using trade data from the UN COMTRADE database [Colour figure can be viewed at wileyonlinelibrary.com]

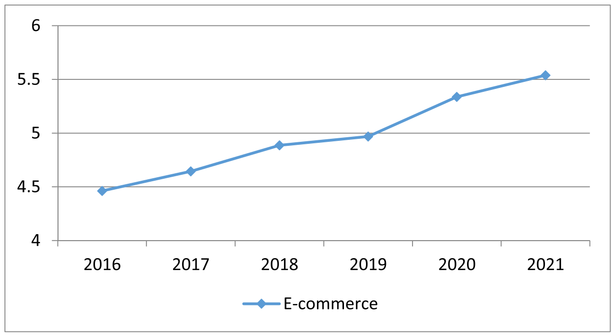


**FIGURE A7** The evolution of e-commerce in the European countries, 2019–2021. *Source*: European Commission – https://digital-strategy.ec.europa.eu/en [Colour figure can be viewed at wileyonlinelibrary.com]

## APPENDIX C

**TABLE C1** The impact of the Covid-19 pandemic on exports in the short and long run.

| Variable | (1) EXP | (2) EXP | (3) EXP | (4) EXP | (5) EXP | (6) EXP |
|---|---|---|---|---|---|---|
| RGDPC | 1.059 | 0.587 | 1.011 | 1.128 | 0.868 | 1.106 |
| | (10.27)*** | (5.77)*** | (9.87)*** | (10.74)*** | (6.63)*** | (10.50)*** |
| INFL | −0.038 | −0.039 | −0.039 | −0.031 | −0.032 | −0.030 |
| | (6.72)*** | (7.24)*** | (6.79)*** | (5.53)*** | (5.92)*** | (5.68)*** |
| WUI | −0.161 | −0.186 | −0.174 | −0.105 | −0.125 | −0.112 |
| | (2.70)*** | (3.25)*** | (2.93)*** | (1.79)* | (2.19)** | (1.89)* |
| STR | −0.032 | −0.008 | — | — | — | — |
| | (4.85)*** | (1.59)* | — | — | — | — |
| DESI | — | 0.523 | — | — | 0.396 | — |
| | — | (4.18)*** | — | — | (2.65)*** | — |
| DESI × STR | — | — | 0.049 | — | — | — |
| | — | — | (2.21)** | — | — | — |
| GOV-RESP | — | — | — | −0.023 | −0.002 | — |
| | — | — | — | (4.26)*** | (1.48)* | — |
| DESI × GOV | — | — | — | — | — | 0.033 |
| | — | — | — | — | — | (2.16)** |
| Error correction (Phi) | −0.587 | −0.597 | −0.591 | −0.595 | −0.596 | −0.598 |
| | (12.03)*** | (12.45)*** | (12.42)*** | (11.78)*** | (12.08)*** | (11.97)*** |
| D.RGDPC | 1.353 | 1.445 | 1.458 | 1.836 | 1.773 | 1.856 |
| | (4.25)*** | (4.63)*** | (4.48)*** | (5.19)*** | (5.31)*** | (5.22)*** |
| D.INFL | −0.009 | −0.008 | −0.010 | −0.007 | −0.005 | −0.008 |
| | (2.54)** | (2.55)** | (2.64)*** | (1.97)** | (1.47) | (2.13)** |
| D.WUI | −0.044 | −0.046 | −0.043 | −0.039 | −0.038 | 0.040 |
| | (1.93)* | (2.06)** | (1.96)* | (1.48) | (1.56) | (1.51) |
| D.STR | −0.118 | −0.112 | — | — | — | — |
| | (5.93)*** | (5.32)*** | — | — | — | — |
| D.DESI | — | 0.296 | — | — | 0.405 | — |
| | — | (2.72)* | — | — | (2.25)** | — |
| D.DESI × STR | — | — | −0.095 | — | — | — |
| | — | — | (5.59)*** | — | — | — |
| D.GOV-RESP | — | — | — | −0.084 | −0.078 | — |
| | — | — | — | (4.41)*** | (4.03)*** | — |
| D.DESI × GOV | — | — | — | — | — | −0.054 |
| | — | — | — | — | — | (3.73)*** |
| Constant | 2.913 | 4.115 | 3.064 | 2.751 | 3.367 | 2.832 |
| | (11.40)*** | (12.09)*** | (11.80)*** | (11.25)*** | (11.61)*** | (11.42)*** |
| Observations | 1085 | 1085 | 1085 | 1085 | 1085 | 1085 |

*Note*: Absolute value of $z$ statistics in parentheses.
*Significant at 10%;
**Significant at 5%;
***Significant at 1%.

TABLE C2 The impact of the Covid-19 pandemic on imports in the short and the long run.

| Variable | (1) IMP | (2) IMP | (3) IMP | (4) IMP | (5) IMP | (6) IMP |
|---|---|---|---|---|---|---|
| RGDPC | 1.432 | 1.067 | 1.406 | 1.533 | 1.246 | 1.507 |
| | (13.60)*** | (6.65)*** | (13.29)*** | (14.46)*** | (8.93)*** | (14.09)*** |
| INFL | 0.046 | 0.047 | 0.050 | 0.035 | 0.038 | 0.036 |
| | (7.68)*** | (7.97)*** | (7.75)*** | (6.25)*** | (6.81)*** | (6.40)*** |
| WUI | −0.195 | −0.203 | −0.206 | −0.108 | −0.113 | −0.116 |
| | (3.38)*** | (3.65)*** | (3.58)*** | (1.87)* | (2.09)** | (1.99)** |
| STR | −0.027 | −0.006 | — | — | — | — |
| | (4.25)*** | (1.46)* | — | — | — | — |
| DESI | — | 0.371 | — | — | 0.422 | — |
| | — | (2.69)** | — | — | (3.06)*** | — |
| DESI × STR | — | — | 0.048 | — | — | — |
| | — | — | (1.95)** | — | — | — |
| GOV-RESP | — | — | — | −0.020 | −0.009 | — |
| | — | — | — | (2.80)*** | (1.81)* | — |
| DESI × GOV | — | — | — | — | — | 0.036 |
| | — | — | — | — | — | (1.72)* |
| Error correction (Phi) | −0.549 | −0.559 | −0.548 | −0.545 | −0.554 | −0.547 |
| | (13.85) *** | (14.19) *** | (13.82) *** | (13.06) *** | (13.29) *** | (13.12) *** |
| D.RGDPC | 1.202 | 1.327 | 1.262 | 1.575 | 1.542 | 1.599 |
| | (3.69)*** | (3.99)*** | (3.82)*** | (4.79)*** | (4.85)*** | (4.99)*** |
| D.INFL | 0.012 | 0.011 | 0.010 | 0.009 | 0.009 | 0.010 |
| | (3.69)*** | (3.42)*** | (3.76)*** | (3.24)*** | (2.51)** | (3.39)*** |
| D.WUI | −0.065 | −0. 069 | −0.058 | −0.051 | −0.052 | −0.056 |
| | (3.63)*** | (3.70)*** | (3.65)*** | (1.96)** | (1.88)* | (2.08)** |
| D.STR | −0.090 | −0.085 | — | — | — | — |
| | (5.40)*** | (5.08)*** | — | — | — | — |
| D.DESI | — | 0.315 | — | — | 0.375 | — |
| | — | (2.41)** | — | — | (2.87)*** | — |
| D.DESI × STR | — | — | −0.069 | — | — | — |
| | — | — | (4.31)*** | — | — | — |
| D.GOV-RESP | — | — | — | −0.118 | −0.110 | — |
| | — | — | — | (7.94)*** | (7.39)*** | — |
| D.DESI × GOV | — | — | — | — | — | −0.051 |
| | — | — | — | — | — | (6.52)*** |
| Constant | 1.790 | 2.671 | 1.853 | 1.533 | 2.183 | 1.604 |
| | (12.09)*** | (13.26)*** | (12.22)*** | (11.01)*** | (11.97)*** | (11.21)*** |
| Observations | 1085 | 1085 | 1085 | 1085 | 1085 | 1085 |

*Note*: Absolute value of $z$ statistics in parentheses.
*Significant at 10%;
**Significant at 5%;
***Significant at 1%.

**TABLE C3** The impact of the Covid-19 pandemic on total trade in the short and the long run.

| Variable | (1) TRADE | (2) TRADE | (3) TRADE | (4) TRADE | (5) TRADE | (6) TRADE |
|---|---|---|---|---|---|---|
| RGDPC | 1.255 | 0.581 | 1.225 | 1.325 | 1.096 | 1.305 |
| | (12.29)*** | (4.97)*** | (11.97)*** | (12.94)*** | (8.29)*** | (12.67)*** |
| INFL | −0.042 | −0.046 | −0.043 | −0.034 | −0.035 | −0.035 |
| | (7.65)*** | (8.20)*** | (7.66)*** | (6.31)*** | (6.73)*** | (6.45)*** |
| WUI | −0.171 | −0.208 | −0.185 | −0.101 | −0.107 | −0.111 |
| | (3.00)*** | (3.79)*** | (3.27)*** | (1.78)* | (1.99)** | (1.95)* |
| STR | −0.026 | −0.009 | — | — | — | — |
| | (4.28)*** | (1.71)* | — | — | — | — |
| DESI | — | 0.592 | — | — | 0.362 | — |
| | — | (4.91)*** | — | — | (2.66)*** | — |
| DESI × STR | — | — | 0.042 | — | — | — |
| | — | — | (3.68)*** | — | — | — |
| GOV-RESP | — | — | — | −0.021 | −0.005 | — |
| | — | — | — | (2.98)*** | (1.68)* | — |
| DESI × GOV | — | — | — | — | — | 0.033 |
| | — | — | — | — | — | (2.55)** |
| Error correction (Phi) | −0.563 | −0.570 | −0.565 | −0.560 | −0.567 | −0.563 |
| | (12.38) *** | (13.50) *** | (12.56) *** | (11.68) *** | (11.91) *** | (11.77) *** |
| D.RGDPC | 1.285 | 1.461 | 1.364 | 1.702 | 1.658 | 1.722 |
| | (4.07)*** | (4.60)*** | (4.24)*** | (5.14)*** | (5.19)*** | (5.17)*** |
| D.INFL | −0.011 | −0.011 | −0.011 | −0.009 | −0.008 | −0.009 |
| | (3.33)*** | (3.64)*** | (3.41)*** | (2.88)*** | (2.43)** | (3.02)*** |
| D.WUI | −0.056 | −0.059 | −0.057 | −0.047 | −0.047 | −0.048 |
| | (3.39)*** | (3.62)*** | (3.43)*** | (2.70)*** | (2.78)*** | (2.73)*** |
| D.STR | −0.102 | −0.093 | — | — | — | — |
| | (6.12)*** | (5.42)*** | — | — | — | — |
| D.DESI | | 0.247 | — | — | 0.395 | — |
| | | (1.80)* | — | — | (2.91)*** | — |
| D.DESI × STR | — | — | −0.072 | — | — | — |
| | — | — | (5.35)*** | — | — | — |
| D.GOV-RESP | — | — | | −0.105 | −0.100 | — |
| | — | — | — | (2.88)*** | (8.01)*** | — |
| D.DESI × GOV | — | — | — | — | — | −0.089 |
| | — | — | — | — | — | (6.26)*** |
| Constant | 2.469 | 4.112 | 2.559 | 2.275 | 2.811 | 2.342 |
| | (11.58)*** | (13.17)*** | (11.80)*** | (11.04)*** | (11.43)*** | (11.16)*** |
| Observations | 1085 | 1085 | 1085 | 1085 | 1085 | 1085 |

*Note*: Absolute value of $z$ statistics in parentheses.
*Significant at 10%;
**Significant at 5%;
***Significant at 1%.

**TABLE C4** The impact of the Covid-19 pandemic and the Global Financial Crisis on international trade (GMM method).

| Period | 2000 → 2011 | | | 2011 → 2021 | | | 2000 → 2021 | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | (1) EXP | (2) IMP | (3) TRADE | (4) EXP | (5) IMP | (6) TRADE | (7) EXP | (8) IMP | (9) TRADE |
| L. | 0.560 | 0.567 | 0.562 | 0.831 | 0.203 | 0.240 | 0.679 | 0.279 | 0.322 |
| | (42.72)*** | (28.25)*** | (32.19)*** | (70.37)*** | (12.36)*** | (14.80)*** | (10.39)*** | (21.49)*** | (28.16)*** |
| RGDPC | 0.633 | 0.766 | 0.657 | 0.412 | 0.626 | 0.517 | 0.425 | 0.863 | 0.854 |
| | (27.63)*** | (18.67)*** | (22.64)*** | (24.17)*** | (32.28)*** | (32.02)*** | (38.32)*** | (36.72)*** | (40.92)*** |
| EF-GOV | −0.037 | −0.043 | −0.006 | −0.907 | −1.268 | −1.070 | −0.433 | −0.907 | −0.848 |
| | (1.96)** | (1.78)* | (2.12)** | (18.97)*** | (19.76)*** | (19.59)*** | (18.34)*** | (16.83)*** | (18.03)*** |
| STAB | −0.273 | −0.384 | −0.349 | −0.044 | 0.209 | 0.154 | −0.064 | −0.091 | −0.068 |
| | (9.77)*** | (8.83)*** | (9.59)*** | (2.34)** | (4.61)*** | (3.68)*** | (3.94)*** | (2.45)** | (2.10)** |
| COR | −0.024 | −0.012 | −0.017 | −0.042 | −0.073 | −0.085 | −0.041 | −0.054 | −0.051 |
| | (5.96)*** | (2.08)** | (3.45)*** | (6.82)*** | (5.10)*** | (6.44)*** | (18.14)*** | (10.72)*** | (12.31)*** |
| FCRISIS | −0.042 | −0.030 | −0.038 | — | — | — | −0.036 | −0.027 | −0.030 |
| | (8.68)*** | (4.43)*** | (6.34)*** | — | — | — | (8.92)*** | (10.37)*** | (11.98)*** |
| DCOVID | — | — | — | −0.031 | −0.025 | −0.028 | −0.014 | −0.023 | −0.018 |
| | — | — | — | (3.73)*** | (11.95)*** | (10.34)*** | (2.75)** | (6.77)*** | (6.97)*** |
| Constant | 1.831 | 1.928 | 2.088 | 0.423 | 3.627 | 3.743 | 1.581 | 4.212 | 3.911 |
| | (12.43)*** | (8.63)*** | (10.87)*** | (3.03)*** | (13.96)*** | (15.28)*** | (25.44)*** | (29.64)*** | (31.57)*** |
| Observations | 1720 | 1720 | 1720 | 1720 | 1720 | 1720 | 3480 | 3480 | 3480 |
| Number of rep_code | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| AR(1) | −4.58 | −4.39 | −4.62 | −4.37 | −4.55 | −4.53 | −4.73 | −4.64 | −4.70 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| AR(2) | −0.44 | 0.92 | 0.24 | −0.69 | −1.05 | −0.87 | 0.10 | −0.60 | 0.39 |
| | (0.663) | (0.359 | (0.809) | (0.489) | (0.292) | (0.385) | (0.923) | (0.552) | (0.693 |
| Sargan test | 0.27 | 0.46 | 0.39 | 18.89 | 13.48 | 15.47 | −0.46 | 14.43 | 0.54 |
| | (0.790) | (0.644) | (0.693) | (0.134) | (0.411) | (0.279) | (0.644) | (0.344) | (0.463) |

*Note*: Absolute value of *t* statistics in parentheses.
*Significant at 10%;
**Significant at 5%;
***Significant at 1%.

**TABLE C5** The impact of the Covid-19 pandemic and the Global Financial Crisis on international trade (PCSE method).

| Period | 2000 → 2010 | | | 2011 → 2021 | | | 2000 → 2021 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Variable** | **(1) EXP** | **(2) IMP** | **(3) TRADE** | **(4) EXP** | **(5) IMP** | **(6) TRADE** | **(7) EXP** | **(8) IMP** | **(9) TRADE** |
| RGDPC | 1.718 | 1.407 | 1.547 | 1.334 | 1.122 | 1.244 | 1.553 | 1.285 | 1.415 |
| | (31.13)*** | (30.98)*** | (31.68)*** | (30.16)*** | (30.23)*** | (33.37)*** | (29.32)*** | (30.15)*** | (31.91)*** |
| EF-GOV | −0.331 | −0.181 | −0.237 | −0.064 | 0.006 | −0.025 | −0.191 | −0.083 | −0.126 |
| | (8.97)*** | (7.45)*** | (8.47)*** | (i.94)** | (3.12)*** | (3.43)*** | (5.13)*** | (3.04)*** | (4.10)*** |
| STAB | −0.169 | −0.187 | −0.184 | −0.178 | −0.211 | −0.204 | −0.162 | −0.191 | −0.184 |
| | (7.35)*** | (8.99)*** | (8.39)*** | (7.19)*** | (9.21)*** | (9.59)*** | (8.92)*** | (11.72)*** | (11.01)*** |
| COR | −0.044 | −0.031 | −0.036 | −0.023 | −0.018 | −0.020 | −0.032 | −0.023 | −0.026 |
| | (10.26)*** | (10.56)*** | (10.54)*** | (4.66)*** | (4.82)*** | (4.71)*** | (9.64)*** | (9.86)*** | (9.76)*** |
| FCRISIS | −0.140 | −0.063 | −0.090 | — | — | — | −0.121 | −0.053 | −0.080 |
| | (2.35)** | (2.49)** | (2.05)** | — | — | — | (3.25)*** | (2.06)** | (2.75)*** |
| DCOVID | — | — | — | −0.076 | −0.050 | −0.061 | −0.063 | −0.048 | −0.055 |
| | — | — | — | (3.64)*** | (2.37)** | (2.82)*** | (6.34)*** | (3.95)*** | (4.85)*** |
| Constant | 2.958 | 4.395 | 4.064 | 4.550 | 5.587 | 5.326 | 3.632 | 4.895 | 4.604 |
| | (12.49)*** | (22.57)*** | (19.39)*** | (22.93)*** | (33.09)*** | (31.56)*** | (21.28)*** | (33.40)*** | (29.91)*** |
| Observations | 1760 | 1760 | 1760 | 1760 | 1760 | 1760 | 3520 | 3520 | 3520 |
| Number of rep_code | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |

*Note*: Absolute value of $z$ statistics in parentheses.
*Significant at 10%;
**Significant at 5%;
***Significant at 1%.