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Does Research and Development Influence Balance of Trade? A Noble GMM-PVAR Analysis

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Abstract

Research Originality: Research and development expenditure (RDE) is essential for international trade to evolve continuously, especially during the fourth industrial revolution (4IR). Despite this significance, research on RDE and balance of trade (BOT) must be substantially improved. To the best of our knowledge, this study is the first to investigate the RDE-BOT nexus.

Research Objectives: This study aims to investigate the causal relationship between RDE and the balance of trade (BOT).

Research Methods: Using panel data of 64 countries, we analyse RDE-BOT relationship by employing the generalized method of moment panel vector autoregressive (GMM-PVAR) techniques.

Empirical Results: The results show that RDE and BOT affect each other. RDE may initially have a detrimental effect on BOT; however, investment in RDE improves export competitiveness and thereby upholds BOT.

Implications: Overall, the findings offer a nuanced understanding of RDE's potential benefits on trade outcomes and guide policymakers seeking to optimize their countries' trade positions in an increasingly globalized and knowledge-intensive economy.

Keywords:

balance of trade; research and development; GMM-PVAR

How to Cite:

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INTRODUCTION

The BOT of a country, which is determined by its net export, is a crucial indicator for gauging its economic performance (Ahad, 2017), and to ensure a positive net export, RDE plays an important role (Sandu & Ciocanel, 2014). RDE, to address the contemporary challenges and foster growth during the 4IR, has become an unavoidable economic consideration, which, for its significance in the export market, has reached \$1.7 trillion across the globe.

RDE, by affecting production capacity and participation in international trade, may substantially influence a country's trade balance. Particularly, by facilitating efficiency, quality of manufacturing activity, and advancement of goods and services, RDE can foster export diversification, e-commerce and e-trade, supply chain efficiency, and practical resource usage, ultimately reducing a negative trade balance (TEAM, 2023).

RDE-based innovations, which are more radical than non-RDE-based, generate products or services of a more significant innovation depth and provide more robust insulation against economic crises (Laursen & Salter, 2006). Though the outbreak of COVID-19, which has caused a 3.2% decrement in the global economy during mid-2020 (UN, 2020), the investment in RDE has exhibited a consistent average annual growth of 4.7% over the past decade (UIS, 2022), which indicates that countries have recognized the crucial role of RDE to facilitate economic recovery and foster sustainable growth in the face of various economic difficulties.

Theoretical studies also suggest that RDE reduces technological gap and endorses efficiency, innovation, and quality, gives birth to new products with competitive advantages, and leads to export growth (Grossman & Helpman, 1990; Keesing, 1967). Researchers have made a number of empirical attempts to investigate these theoretic claims, who have recognized RDE as a factor that influences product and process innovation of exporting firms, which produces superior return returnsporting concerns than domestic sales (Peters & Roberts, 2022). Following this higher payoff, exporting firms allocate higher RDE than domestic firms, endogenously generating higher productivity growth rates and boosting export performance (Aw et al., 2011). Even small and medium-sized firms' participation (SMEs) significantly and positively depends on the RDE-sales ratio (Falk & de Lemos, 2019). Especially in the case of manufacturing firms, RDE helps to innovate technologies and introduce better processes, which can make production easier (Souder & Padmanabhan, 1989; Van Beveren & Vandenbussche, 2010)and more efficient (Haaland & Kind, 2008). Besides, the high-tech industry is highly involved in RDE, where there is a positive correlation between total RDE and the level of exports with the dominance of private RDE (Sandu & Ciocanel, 2014).

The relationship between RDE, production, and export performance can better define the export scenario. RDE has a larger impact on productivity both in the present and future (Antonietti & Cainelli, 2011; Halpern & Muraközy, 2012; Ricci & Trionfetti, 2012). Quality is one of the prerequisites to attain export success and productivity (Lages et al., 2009), which can be maintained through product differentiation, where RDE plays a key role (Lin & Saggi, 2002).

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Theories and empirical evidence indicate that companies invest in RDE to differentiate products and services from competitors and to sustain in the competitive market(Cellini & Lambertini, 2002; Grossman & Helpman, 1990). Higher productivity, advanced production processes, contemporary technologies, and product differentiation together sponsor a firm as well as an economy to export more, which suggests RDE has a positive correlation with export performance (Barrios et al., 2003; Carboni & Medda, 2018; Girma et al., 2008; Ito & Pucik, 1993).

Unlike the RDE-export relationship, RDE's relationship with import has been researched with a niche orientation for special aspects. Theoretical propositions regarding the RDE-import link are mixed, which suggests that depending on the legality and cost, parallel import, in general, might influence firms to reduce RDE (Li & Maskus, 2006), though cheaper R&D fuels imports of inputs and liberalization and easy access to inputs might stimulate RDE (Bøler et al., 2015), especially for high-tech industries import competition might elevate RDE (Zietz & Fayissa, 1992). The empirical discourse encompasses a few studies that have discussed the relationship between technology import and RDE. Scholars argue that, in some instances, RDE and technology imports are symbiotic in terms of innovation strategy. Technology import is considered beneficial for RDE because of its innovation benefits and process modification, which can increase productivity (Chang & Robin, 2006; Gonchar & Kuznetsov, 2018). However, importing technology by firms with formal research institutes does not complement the RDE; instead, in the presence of international innovation technology, importing substitutes RDE (Lee, 1996) and emphasizing domestic RDE efforts tend to reduce the reliance on importing technology (Kim & Stewart Jr, 1993). Moreover, importer firms are found to have higher RDE than non-importer firms (Katrak, 1989), and import competition induces RDE to be reallocated towards more productive and profitable firms (Xu & Gong, 2017).

However, aside from the growth of worldwide RDE and its significance in achieving a positive trade balance, the impact of RDE on BOT still needs to be explored, with just a few studies on RDE's impact on either exports or imports providing an incomplete picture. This study aims to shed light on the causal relationship between RDE and BOT for an unbalanced panel of 64 countries covering the period 1996 to 2020 to address this empirical exigency and lack of systematic investigation regarding the direct relationship between RDE and BOT using advanced econometric techniques, GMM-PVAR.

The contribution of this study is multidimensional. We have investigated the relationship between RDE and BOT, while most of the previous research has investigated the impact of RDE on either import or export performance only. Studying BOT in this context, instead of considering either export or import individually, enables us to address the existing trade-RDE debate by offering findings that link both export and import to the research and development activity in a single setup.

Moreover, studies discussing the RDE-import relationship have primarily focused on the technology import, whereas we have considered BOT. Therefore, this study complements the previous studies by encompassing the holistic export-import tendency of the selected economies.

To our knowledge, this paper is the first of this nature. Empirically, we explored the unique importance of RDE as a favorable contributor to achieving a positive BOT. Integrating RDE as a catalyst of innovation and competitiveness can significantly influence a country's net exports. Though RDE may initially be disruptive to the BOT, a nation should actively partake in RDE, recognizing its impact and potential to tap into overseas trade and global economic trends. RDE generates synergy by driving improvements and efficiencies.

Additionally, unlike previous research, this study adds to the current literature with results derived by advanced econometric methodologies such as GMM-PVAR. The findings, inferring the causality between RDE and BOT, help better understand RDE's distinct implications and guide policy circles in developing appropriate strategies for improving the economic performance of the selected nations.

METHODS

Due to the availability of RDE data, we use an unbalanced panel of 64 countries and years ranging from 1996 to 2020 to examine the causal relationship between RDE and BOT. The Data for RDE and BOT are sourced from the World Bank. Inspired by the trade theory of the technology gap, numerous research initiatives have been undertaken to investigate the relationships between innovation or RDE and trade. However, due to the need for studies investigating the holistic measure of trade, we investigate the relationship between RDE and BOT using the GMM-PVAR estimation. The primary justification behind our utilization of GMM-PVAR is to investigate the endogenous link between RDE and BOT. Second, the complex interaction between RDE and BOT will be deciphered with the help of panel Granger causality analysis, which allows for considering the potential of both unidirectional and bidirectional causalities. Impulse response functions (IRF) can be utilized to analyze the dynamic links between RDE and BOT.

In order to have a better understanding of the variables, we begin the GMM-PVAR analysis by doing several panel unit-root tests. The construction of the GMM-PVAR model continues with the following phase: determining the appropriate lag order for the variables. The degree of freedom is decreased when the lag order is too long, and the sample may appear skewed. When determining whether delayed order is optimal, we take into consideration the characteristics of the sample and use the Akaike information criterion (AIC), the Schwarz criterion (SC), and the Hannan and Quinn information criteria (HQIC). After that, we applied the GMM-PVAR model in the following way: Y_{it} = [Research and development expenditure $_{it}$, Balance of trade $_{it}$] is a vector of k endogenous variables for country i at time t. The reduced form of the dynamic relationship among the endogenous variables can be described by:

$$Y_{it} = A_{0i} + A(\ell)Y_{it-1} + e_{it}$$
$$i \in \{1, 2, \ldots, N\},\ t \in \{1, 2, \ldots, T_i\} \qquad (1)$$

where A_{0i} is a 1×k vector of time-invariant country-specific intercepts, $A(\ell)$ are k×k matrices of lagged coefficients, $A(\ell) = \sum_{j=1}^{p} (A_{j\,j-1})$, that collect the own and cross-

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effects of the ℓ lag of the dependent variable on their current observations. Finally, e_{it} is a 1 × k vector of idiosyncratic disturbances where $E(e_{it}) = 0$, $E(e_{it,}\ \acute{e}_{it}) = \Sigma_e$ (being Σ_e a nonsingular matrix) and $E(e_{is,}\ \acute{e}_{is}) = 0$ for t≠s.

RESULTS AND DISCUSSION

Descriptive statistics

Descriptive statistics reveal the statistical parameters of the variables used in the study (see Table 1). BOP is characterized by a large variation across the observation, with a standard deviation of 94547.028 and a mean of 4902.31. This large variation is attributed to the wide range of trade balance encompassing the trade deficit of the USA, amounting to -763533 in 2006, to China's trade surplus, amounting to 358572.63 in 2000. The reasons for such variations in trade balances among countries are, on the one hand, large government spending, strong domestic demand, cheap international alternatives, home overconsumption than domestic production, low rate of domestic savings relative to investment needs, and on the other, greater demand for a country's goods and services at the global market, edge over others in producing and exporting of particular goods, undervalued home currency, and cheaper exports. Regarding RDE, though some countries are found to be less research-focused compared to others (Colombia has an RDE of 0.131), relative to BOP, RDE is less dispersed, with a standard deviation and mean of 0.996 and 1.629, respectively.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max.
BOP	1625	4902.31	94547.028	-763533	358572.63
RDE	1518	1.629	0.996	0.131	5.436

To investigate the causality between RDE and BOT, first, we take log of both the variables and identify the panel unit-root of them (see Table 2). Before estimating the GMM-PVAR, we check out the panel unit-root of the variables. We perform both first- (Table 2) and Pesaran's second-generation (Pesaran, 2007) tests. The result of Pesaran's second generations shows in Table 3. While first-generation tests need variables to be independent across nations in order to calculate unit-root, which is typically difficult to do for co-movements of macroeconomic variables, second-generation test (Pesaran, 2007) allows for cross-sectional reliance of variables in a panel. The results reveal that all variables with and without trend at their first differences have stationarity.

Choosing the right lag-order is crucial when performing a GMM-PVAR analysis. Lag shorter than the minimum needed to meet the criteria may not adequately explain the system's mechanics and may also add bias to the results due to missing or neglected factors (Boubtane et al., 2013). Besides, over-parameterization may occur if there are unwarranted lags in data collection. In light of this, we select the second-order GMM-PVAR model using the overall coefficient of determination as given by Akaike information criterion (AIC), Schwarz criterion (SC) and Hannan and Quinn information criterion (HQIC) (Andrews & Lu, 2001). Since OLS estimation may provide biased coefficients in dynamic models, we employ the generalized method of moments (GMM) to do the estimation. Furthermore, we transform all the variables using forward mean differencing or orthogonal deviations (Abrigo & Love, 2016; Love & Zicchino, 2006) and to remove the fixed effects, which are correlated with regressors (Gabriel & de Santana Ribeiro, 2019).

Table 2. First-generation panel unit-root test

Variables	No trend		Trend		Cross Sections	Observations
	Statistic	Prob	Statistic	Prob		
Panel A: Augmented Dickey–Fuller unit-root test						
logRDE	119.2693	0.7399	141.7124	0.2276	65	1518
ΔlogRDE	564.0554	0.0000	469.9221	0.0000	65	1453
logBOT	129.7710	0.4892	123.0526	0.6544	65	1625
ΔlogBOT	751.2383	0.0000	578.9709	0.0000	65	1560
Panel B: Phillips–Perron unit-root test						
logRDE	130.0606	0.4820	122.2152	0.6741	65	1518
ΔlogRDE	1016.5847	0.0000	899.1753	0.0000	65	1453
logBOT	117.4831	0.7767	124.3738	0.6227	65	1625
ΔlogBOT	1129.6121	0.0000	900.2099	0.0000	65	1560
Panel C: Im–Pesaran–Shin unit-root test						
logRDE	7.1442	1.0000	4.0771	1.0000	65	1518
ΔlogRDE	-19.1504	0.0000	-6.2638	0.0000	65	1453
logBOT	0.6449	0.7405	-1.5382	0.0620	65	1625
ΔlogBOT	23.3046	0.0000	-19.3334	0.0000	65	1560

The null hypothesis is that the variable follows a unit-root process.

Table 3. Pesaran Second-generation panel unit-root test

Variables	No trend		Trend		Cross Sections	Observations
	Statistic	Prob	Statistic	Prob		
logRDE	-0.703	0.241	2.875	0.998	65	1518
ΔlogRDE	-8.067	0.000	-6.007	0.000	65	1453
logBOT	1.315	0.906	1.042	0.851	65	1625
ΔlogBOT	-10.019	0.000	-5.768	0.000	65	1560

The null hypothesis is that the variable follows a unit-root process.

We analyze the causal link between yearly RDE expenditures and BOT in order to shed insight on the nature of the relationship that exists between them. The relationship between RDE and BOT is shown in Table 4, and the findings show that BOT has a positive impact on RDE in the first lag, while RDE has significant adverse effects on BOT in the second lag. The possible reason behind these findings could be that higher BOT may insist the authorities invest heavily in RDE, while RDE may require the

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purchase of different equipment and materials to facilitate research, which may lead to higher imports and unfavorable BOT.

Table 4. GMM-PVAR estimation

Response of	Response to	
	$logBOT_t$	$logRDE_t$
$logBOT_{t-1}$	0.003	0.046***
	(0.096)	(0.011)
$logBOT_{t-2}$	-0.166*	0.016
	(0.096)	0.012
$logRDE_{t-1}$	0.226	0.325
	(0.461)	(0.240)
$logRDE_{t-2}$	-0.795**	0.043
	(0.393)	(0.097)
Hansen p-value	0.79	

Two variable VAR model is estimated by GMM, country-time and fixed effects are removed prior to estimation. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

After the unit-root tests and the GMM-PVAR estimations, we make use of the GMM-PVAR Granger causality test with the goal to evaluate if RDE causes BOT or vice versa. Table 5 contains the outcome of the granger test to determine whether or not a causal relationship exists as well as an explanation of the causal link between RDE and BOT.

Table 5. VAR granger causality results

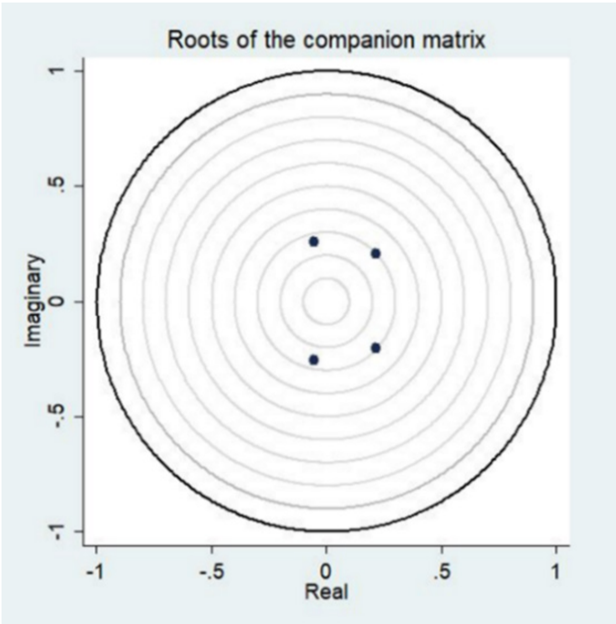
Causal direction	Chi-square	df	p-value
logBOT → logRDE	15.894	1	0.000
logRDE → logBOT	6.056	1	0.048

The null hypothesis that BOT does not granger-cause RDE is rejected with 99% confidence and the null hypothesis that RDE does not granger-cause BOT is rejected with 95% certainty. On the basis of the results of these GMM-PVAR granger causality tests, one can conclude that RDE and BOT have a two-way relationship.

Even if identifying limits are imposed on the parameter estimations, the coefficients of the GMM-PVAR in reduced form cannot be interpreted as causal links (Abrigo & Love, 2016). To circumvent this limitation, we conduct additional research employing the impulse response function (IRF) and the forecast-error variance decomposition (FEVD). However, before determining IRF and FEVD, we first investigate the GMM-PVAR stability criterion. Since each of the eigenvalues of the estimated coefficient matrix are less than one and lie within the unit circles (Figure 1), which are depicted on the RDE stability graph, we conclude that the estimates are stable. This indicates the accuracy of the estimates.

In the subsequent phase, we compute the IRF to explain the response of RDE or BOT to a perturbation in another related variable, presuming that the magnitude of all other shocks is equal to zero. Figure 2 depicts the IRF, with the shaded regions representing the 95% confidence interval and the solid lines representing the orthogonal IRF of the relevant variable over five years. The IRF confidence intervals are derived from the distribution of the fitted reduced form of the GMM-PVAR model and are based on the outcomes of 200 Monte Carlo simulations. During our discussion of the findings, our primary focus will be the connection between RDE and BOT, which is of significant importance to us.

Figure 1. Stability Graph



The reactions of RDE and BOT to a jolt in RDE and BOT, respectively, may be found in the left column and the right column of the IRF diagram shown in Figure 2. According to this graphical depiction (second row, first column of figure-2), the relationship between RDE and BOT is nonlinear; RDE first exerts a negative influence, followed by a brief positive effect that converses to zero.

The possible explanation that is compatible with these findings might be that initially, RDE may have a detrimental effect on BOT due to the fact that RDEis very technology-heavy and necessitates the use of nonrenewable energy sources like oil, gas, coal, etc., which may not be readily accessible domestically. Because of this, nations that put a lot of effort into RDE can find themselves in a position where they have to import huge quantities of these resources (Chen, 2017). This can lead to an increase in the proportion of a nation's imports to exports, which might make the trade imbalance worse in the short run. Subsequently, investment in RDEleads to greater rates of product and process innovation, which can make the manufacturing process simpler and less expensive (Haaland & Kind, 2008; Souder & Padmanabhan, 1989; Van Beveren & Vandenbussche, 2010). Another possible explanation consistent with these findings could be that RDE

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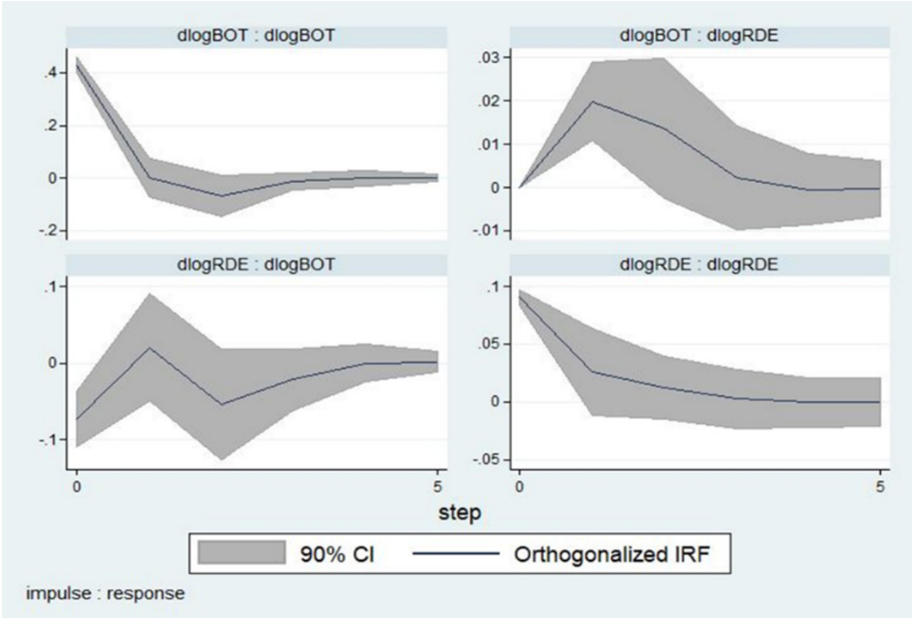
Figure 2. IRF plot



leads to higher product and process innovation rates in developing countries. Therefore, it increases export performance (Antonietti & Cainelli, 2011; Halpern & Muraközy, 2012; Ricci & Trionfetti, 2012) for exporting enterprises with a higher economic return on sales to export markets than sales to domestic markets (Aw et al., 2011; Peters & Roberts, 2022). This condition is because exporting firms with a higher economic return on sales to export markets have a greater incentive to sell their products abroad. As a result, RDE has a beneficial impact on the overall trade balance.

On the other hand, a higher BOT always encourages more investment in RDE (first row, second column of Figure 2). This result is obvious, as higher BOT implies higher exports and thus higher foreign exchange earnings for the government, which might motivate them to invest in RDE to increase the earnings further.

Table 6. Variance decomposition analysis

Forecast Horizon	Impulse Variable		Impulse Variable	
	logRDE	logBOT	logRDE	logBOT
	Response on logRDE		Response on logBOT	
2	0.957	0.042	0.030	0.969
4	0.938	0.061	0.046	0.953
6	0.938	0.061	0.046	0.953
8	0.938	0.061	0.046	0.953
10	0.938	0.061	0.046	0.953

After IRF, we evaluate the cumulative contribution of one variable to explaining changes in other variables using FEVD and report the findings in Table 6. The variance decomposition indicates that the aggregate comprehensive BOT of an economy explains

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roughly 6.1% of the variations in RDE, whereas RDE only explains 4.6% of the changes in BOT. According to these findings, RDE and BOT have a reciprocal impact on one another.

CONCLUSION

RDE is crucial in driving innovation and technological advancements and stimulates export performance and overall trade balance. Despite having such importance, studies related to RDE and BOT still need to be included, which warrants further investigation regarding causality and interaction between them. To fill this gap, we explore the RDE and BOT nexus using GMM-PVAR and find that RDE causes BOT and vice versa. Our findings show a dynamic relationship between RDE and the country's trade balance. Though RDE hampers the BOT, it contributes to a favorable trade balance in the long run. This result implies that since RDE needs to import technology and necessary inputs, which may not be readily accessible domestically, it may have a detrimental effect on BOT initially; however, RDE leads to more excellent rates of product and process innovation, which can make the manufacturing process efficient and less expensive and thereby improve export competitiveness and BOT. Similarly, an improved trade balance can provide a conducive environment for increased RDE, which may lead to technological advancements, innovation, and further export growth.

The findings of this study underscore the relevance of RDE for BOT, adding to knowledge related to innovation and trade; yet, our analysis has some limitations. We were unable to analyze the most recent information due to data constraints. Despite the limitation, policymakers can use this knowledge to their advantage. It can empower them to encourage innovation, boost export competitiveness, and promote sustainable trade in today's globalized, knowledge-intensive economy.

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