sustainability

MDPI

Article

How Knowledge Assets Affect the Learning-by-Exporting Effect: Evidence Using Panel Data for Manufacturing Firms

Hyun-Jee Kim and Bongsuk Sung *

Department of International Trade, Kyonggi University, Gwanggyosan-ro, Yeongtong-gu, Suwon-si, Gyeonggi-do 16227, Korea; jhyunk@kgu.ac.kr

* Correspondence: bsssung@kgu.ac.kr; Tel.: +82-31-249-1528; Fax: +82-31-249-9401

Received: 9 March 2020; Accepted: 10 April 2020; Published: 13 April 2020

check for updates

Abstract: Using panel data from Korean manufacturing firms, this study empirically investigates how knowledge assets impact the relationship between exports and productivity. We consider a scenario in which firms are situated in a globally competitive, knowledge-based environment. We establish a dynamic panel vector autoregressive model by considering the outcomes of various panel framework tests. A generalized method of moments estimator is employed to test the dynamic relationships among the variables, and a post-estimation test, Granger causality test, and impulse response test are performed. Our findings indicate the existence of a learning-by-exporting effect on the enhancement of total factor productivity (TFP). The result show that TFP can be improved by interacting with exports and knowledge assets, and that firms' knowledge assets significantly and positively affect their exports. However, industry competition, as an external force, does not contribute to boosting firms' productivity. We highlight the importance of continuously upgrading productivity, exports, knowledge assets, and industry competition by demonstrating that the present levels of these elements serve as the main source of their own future values. Finally, the implications of our results are outlined.

Keywords: knowledge assets; learning-by-exporting effect; dynamic panel approach; manufacturing industry

1. Introduction

Several prominent works, such as Bernard and Jensen [1], Bernard and Wagner [2], Bernard et al. [3], Wagner [4], and Bernard et al. [5], argue that the learning-by-exporting (LBE) effect is a key factor that determines the relevance of exports for companies. Participating in export activities entails a learning process that may impact firms' productivity and innovation. Exporting increases the likelihood of businesses benefiting from knowledge spillovers in overseas markets, thus enabling exporters to engage in more diverse forms of learning than those available to their counterparts that operate only in domestic markets; such diverse learning opportunities may cover advanced technologies, best practices, and valuable knowledge. Enterprises can exploit these opportunities through repeated interactions and information exchanges with foreign agents involved in international business (e.g., customers, competitors, distributors, intermediaries, and even their own networks) [6–8]. This facilitates flexible, rapid, and efficient responses to dynamic, challenging environments [9,10], which can enhance exporters' innovation and productivity compared to non-exporters.

However, empirical findings on the potential LBE effect are mixed [11,12], and several reasons have been cited to explain their inconclusiveness, such as the lack of a coherent theoretical framework that can guide LBE-related empirical research [13], the need for a dataset sufficiently long to enable the detection of LBE effects [7,14], methodological problems [13], such as the role of unobservable factors (e.g., management rather than productivity concerns), the variety of assessment techniques employed, firm heterogeneity, industry- and country-specific (exporting- and partner-based) factors, spillovers to non-exporters, and the role of imports and reallocation effects.

Many researchers have made efforts to evaluate the LBE effect accurately by tackling the issues that cause mixed outcomes. For example, scholars have examined the central question of which factors are the most relevant regarding learning in export activities. As a main driver of sustainable growth amid global knowledge-based competition, LBE is directly linked to increased firm productivity (e.g., [4,6,9,14,15]) and innovation (e.g., [12,16,17]), and it is a primary source of organizations' sustainable competitive advantage. However, the LBE effect and the potential for learning from export activities (often called the "growth premium from exporting") cannot be generated simply by operating in export markets; other [13] firm-, industry-, and country-specific elements are also required.

In this study, we draw on the firm-specific aspect to explain differences in the LBE effect among firms and examine how their knowledge assets influence LBE. As the knowledge economy rapidly evolves and global competition intensifies due to increased trade openness, more attention is being paid to knowledge assets in the global marketplace. In the context of heterogeneous trade theory [11], international competitive and knowledge-based environments force low-productivity companies to shut down. Knowledge assets lead to innovation (e.g., [18,19]) and productivity enhancement (e.g., [20,21]); this is pivotal as knowledge assets constitute one of the most vital firm-specific factors for an organization's sustainable growth. Therefore, we need to distinguish firms according to knowledge assets that are firm-specific when evaluating their growth premium through LBE, because exporting has unbalanced effects across businesses. Key features related to knowledge assets include research and development (R&D), technological (e.g., [6,16,22]) and innovative (e.g., [16,23]) capacities, marketing capacity as an intangible capability (e.g., [16,23]), and absorptive capacity (e.g., [12]).

The literature on LBE effects contributes to the discourse on the relationship between LBE and firm performance, as well as to our understanding of the principal firm-specific factors involved. Nonetheless, theoretical and empirical gaps remain. At least two concerns must be addressed.

First, given the importance of firms' knowledge assets in strengthening productivity, we need to gauge the significance of these assets as a determinant of learning capabilities, which may influence the degree of productivity increase. Research claims that learning is a knowledge acquisition process, and knowledge is an outcome of learning [24,25]. Furthermore, firms aim to accumulate expertise for global expansion [26,27]. However, no study empirically investigates how differences in enterprises' knowledge assets affect the growth premium gained from their export activities.

According to organizational theory, the current proficiency level impacts how businesses assimilate and interpret new understanding that they obtain through learning [28]. As a learning process, firms' export activities in international markets develop dynamically into a fit between their existing knowledge stocks and the new skills attained from such endeavors [29]. An exporter's actual learning generally depends on its absorptive capability [12], defined as the ability to promote the comprehension, assessment, assimilation, and application of new know-how for commercial ends [30]. Absorptive capability entails companies' successful, efficient learning, which determines their learning outcomes. However, an enterprise's absorptive capability depends heavily on its previous expertise and competencies. Thus, knowledge assets—a result of firms' existing and accumulated knowledge gained through exporting—play a crucial role in determining businesses' learning outcomes through exporting. To extend Cohen and Levinthal's [30] argument that absorptive capability is a key factor in firm innovation, we suggest that firms' knowledge assets, often referred to as "intellectual and knowledge capital" or "intangible resources", are essential resources in innovation [31,32] and value creation [33,34] that lead to productivity growth [20,35].

In addition, the literature on the measurement of knowledge assets (e.g., [36–38]) and LBE [16,24] posits that technological capability (measured as R&D expenditure and intangible capability (measured as marketing expenditure) can be considered knowledge assets.

Most knowledge asset models have tried to analyze three components—human, structural, and relational capital—as knowledge assets [36], but quantifying knowledge assets remains a challenge. Determining a company's knowledge assets using objective criteria is difficult, and many approaches have been proposed for this purpose. Using cost indicators has been found to be effective [37,38]. According to Bakhsha et al. [37], Ryu et al. [38], and Hsu and Fang [39], knowledge assets can be evaluated in terms of businesses' spending on human resource development (human capital), the operation of innovation-friendly structures (structural capital), and the maintenance of external relationships, brand value, and reputation (relational capital).

Human capital expenditure comprises firms' spending on enhancing their employees' experience, skills, competence, attitude, creativity, and motivation [18,40,41]; this includes labor costs, executive salaries, bonuses, severance pay, retirement benefits, and stock compensation costs [37,38]. Structural capital expenditure comprises enterprises' spending on sustaining the generation and implementation of employees' valuable ideas in their works [39] by promoting the organization's learning, process, and information achievement [41,42]; this includes R&D spending, ordinary development costs, royalties, book purchasing and printing expenses, education and training costs, computer processing fees, and employee benefits [37,38]. Relational capital expenditure indicates firms' spending on the establishment and advancement of collaboration with external partners. This expenditure enables them to exchange the information and expertise required to conduct innovation activities and overcome the innovation-related risks [43], enhance their brand value and reputation by meeting customer needs and expectations, and perform various marketing activities [41,42,44]; it includes export costs, sales promotion costs, sales commissions, other selling expenses, entertainment fees, advertising costs, storage fees, sample fees, packing costs, carrying costs, overseas market development costs, and customer service costs [37,38].

Considering the components of the three capitals, a firm's knowledge assets represent its comprehensive learning capability, obtained by integrating technological, marketing, and absorptive abilities. Knowledge assets are important for producing value; the goal is to generate more value per unit of investment in each resource [34], which increases productivity [20,35]. Greater mastery from exporting reduces firms' uncertainty and risk, and exporters use new understanding to boost firm performance. Thus, developing export activities directly involves searching for and exploring new areas of expertise that can amplify business performance (e.g., in productivity and innovation).

Second, although panel data have been used to test the LBE hypothesis, the literature lacks a systematic approach. Most panel data studies used for firms are heterogeneous, non-stationary, and co-integrated. In general, there are dynamic paths in production [24,45] and exports [46,47] that lead to path dependence. This means that the present value of productivity and exports depends on their value in the previous period. When employing a panel technique, it is critical to confirm the data's characteristics (e.g., multicollinearity, autocorrelation, structural breaks in the series, cross-sectional dependence and homoscedasticity between and within cross-sectional units, unit roots in individual series, and co-integration between variables). An empirical model should be established by considering the data's characteristics.

Based on the hypothetical extent to which knowledge assets (as a form of firm heterogeneity) influence the relationship between exporting (activities) and productivity enhancement, as well as the methodological concerns discussed above, we perform an econometric analysis on how exporting affects productivity. The remainder of this paper is organized as follows. Section 2 outlines our research model and data measurement. Section 3 covers the source of the data and descriptive statistics. Section 4 presents the empirical results. Section 5 summarizes the main findings and lists the study's implications. Section 6 describes the conclusions.

2. Model Specification and Data Measurement

We explore how exporting affects productivity via the LBE effect based on the hypothetical role of knowledge assets in the relationship between exporting and productivity enhancement. We employ a standard model put forth by Bernard and Jensen [1,48] and scrutinize firms' growth premium from exporting as follows (Equation (1)):

$$TFP_{i,t} = \alpha + \beta EXE_{i,t-p} + \gamma KNW_{i,t-p} + \delta COM_{i,t-p} + \eta_i + \varepsilon_{i,t}, \tag{1}$$

where i is the firm, t is the year, η_i is the unobservable, firm-specific effect, ε is the error term, and *TFP* denotes "total factor productivity." Although the literature argues that LBE directly leads to increased productivity and innovation, productivity measures may be used as a suitable benchmark of learning-by-doing, as productivity improvements might reflect a firm's successful application of new expertise for productive ends (i.e., they may be indicative of productivity growth [34,35,44], which reflects a company's ability to use knowledge in an efficient way to strengthen its operations and produce value). *EXE*, an independent variable, indicates a firm's export status. *KNW*, a control variable, refers to knowledge assets—defined as an organization's intangible assets and capabilities [37,38]; knowledge assets comprise the comprehensive learning capability at the firm level, which accounts for the potential learning effect that may come from exporting and, therefore, an enterprise's potential productivity growth from exporting activities. *COM* indicates industry competition, an industry-specific factor that may influence a company's growth premium from exporting. According to heterogeneous firm trade theory, when dynamic competition in an industry is fierce, productivity is the most vital factor for firm survival. Fierce competition tends to escalate businesses' innovation activities to capture market opportunities by rapidly applying new knowledge [49], which directly contributes to productivity enhancement.

To compute *TFP*, we employ Levinsohn and Petrin's [50] estimator. We follow Levinsohn and Petrin's [50] value added method. Furthermore, we use firms' gross value added to gauge output and intermediate inputs (raw material and energy) as a proxy to avoid the bias caused by the endogeneity problem (which is due to the correlation between the regressors and the error term). The independent variable, a firm's export status (*EXE*), is measured as export volume, following Gross and Helpman's [51] argument that covariance is likely between the intensity of knowledge spillovers across two countries and the intensity of trade. It may take time for the learning gained from exporting to spill back to and be used by companies [16,48,52]. Accordingly, we use lags of our independent variable to eliminate serial correlation in the disturbance. We define a firm's knowledge assets (*KNW*) as an organization's spending on human resource development (human capital), the operation of innovation-friendly structures (structural capital), and the maintenance of external relationships, brand value, and reputation (relational capital) [37–39]. We calculate the costs of the three capital expenditures based on Bakhsha et al. [37] and Ryu et al. [38]. Industry dynamic competition can be measured in terms of industry concentration and openness, which can be established using the Lerner index of market power [53], profit margin [54], the Herfindahl–Hirschman index, and the CR4 (four-firm concentration ratio) index. We use industry openness to quantify industry competition. Industry openness enhances market competition by increasing the number of differentiated products and decreasing prices, which decreases the industry's net profit [55,56]. The reciprocal of the average profit margin, computed by dividing net revenue (total revenue minus total cost, including taxes) by total revenue at the industry level, can be used as a proxy for the industry's dynamic competition [54], similar to the Lerner index of market power.

3. Data Sources and Descriptive Statistics

The primary data used in this study—the annual measures for firms—are taken from the KISValue database provided by NICE Information Services Co., Ltd. (for the descriptive statistic and industry breakdown of the sample, see Tables 1 and 2).

Table 1. Descriptive statistics.

Variable	Mean	Variable	Mean
Total factor productivity (*TFP*)	2.941	Export volume (*EXE*)	3.074
Knowledge assets (*KNW*)	3.922	Reciprocal of profit margin (*COM*)	1.491

Notes: Numbers in cells are the natural logarithms of their original values.

Table 2. Industry breakdown of the sample (1991–2018).

Industry	Observations	Sales	Exports	Value Added	Total Assets	Knowledge Assets	Tangible Assets	Age	Profit Margin
Food products	1185	338.07	6.68	126.09	348.10	45.87	22.32	39.43	20.30
Beverages	271	246.09	1.92	116.26	453.61	59.05	39.39	50.58	9.92
Tobacco products	24	2250.00	353.66	1330.00	4750.00	418.41	228.25	32.00	2.73
Textiles (except apparel)	364	113.79	19.00	24.03	203.87	10.66	10.50	51.42	26.18
Apparel, clothing accessories, and fur articles	533	172.88	1.76	61.40	176.20	26.72	0.54	32.44	23.36
Leather, luggage, and footwear	132	102.17	32.71	22.24	100.45	11.12	2.56	46.00	11.68
Wood and products of wood and cork (except furniture)	110	161.41	6.78	52.04	266.03	13.48	42.17	51.50	96.83
Pulp, paper, and paper products	662	142.14	11.30	38.77	187.35	13.60	42.15	46.41	29.36
Printing and reproduction of recorded media	87	29.05	3.26	10.82	45.30	7.91	2.68	25.72	12.58
Coke, briquettes, and refined petroleum products	137	5040.00	2520.00	2840.00	2600.00	116.03	341.33	47.60	8.53
Chemicals and chemical products (except pharmaceuticals and medicinal chemicals)	2526	498.14	72.33	160.81	567.86	36.50	73.15	35.06	21.36
Pharmaceuticals, medicinal chemicals, and botanical products	2416	68.69	2.41	39.03	109.94	17.72	1,440.00	38.4	13.63
Rubber and plastic products	981	137.03	10.42	46.61	167.16	18.21	19.50	32.43	17.25
Other non-metallic mineral products	932	192.16	3.29	60.66	345.47	22.15	37.83	43.19	27.92
Basic metals	1928	637.94	83.29	187.39	895.59	35.00	201.62	42.20	32.56
Other machinery and equipment	3278	138.88	26.37	51.32	184.01	28.56	7.84	25.62	15.84
Electronic components, computers; visual, sound, and communication equipment	5004	698.81	279.43	282.53	748.21	34.64	130.22	25.84	17.67
Medical, precision, and optical instruments; watches and clocks	1085	41.69	4.66	21.70	61.37	21.58	3.31	15.89	26.70
Electrical equipment	1405	217.54	45.70	72.84	274.85	18.95	17.97	32.13	18.78
Other transport equipment	512	1720.00	502.94	445.82	2280.00	118.45	103.66	22.90	29.18
Furniture	165	150.76	3.63	60.24	135.08	15.85	2.45	32.40	13.93
Other types of manufacturing	163	48.39	9.18	17.54	75.91	8.37	0.65	31.24	13.83
Motor vehicles, trailers, and semitrailers	2218	807.66	219.07	269.74	872.35	97.04	70.61	37.07	28.53
Fabricated metal products (except machinery and furniture)	990	92.63	12.35	31.76	111.51	18.13	9.11	25.63	20.81

Notes: The unit of sales, exports, value added, total assets, knowledge assets, and tangible assets is billion KRW. The unit of age is year. The unit of profit margin is percent. The values (except observations) are the average from 1991 to 2018. The age is the average of the previous year.

The data cover manufacturing firms listed in the South Korean stock market—the Korea Composite Stock Price (KOSPI), Korea Securities Dealers Automated Quotation (KOSDAQ), and Korea New Exchange (KONEX)—from 1991 to 2018. The unbalanced panel dataset contains 27,108 observations. We calculate the data used to determine the variables for productivity, exports, knowledge assets, and industry competition based on 2010 prices. We express all data in logarithmic form. As *EXE* is zero for firms that do not export, we employ *EXE* as the natural log of one, plus export volume.

4. Empirical Analysis

We check the data traits in six steps. First, we check for the presence of multicollinearity. The test indicates that multicollinearity is not a problem in our data, as it adheres to the variance inflation factor (VIF) threshold of less than 10: The VIFs for *EXE*, *KNW*, and *COM* were 1.030, 1.020, and 1.010, respectively. Then, we use Wooldridge's [57] method to check for first-order autocorrelation and find the sign of the autocorrelation (F statistic = 64.224, p = 0.000). Third, we conduct a panel groupwise heteroscedasticity test to check for homoscedasticity within the cross-sectional units. The test reveals the presence of heteroscedasticity by showing that the null hypothesis of homoscedasticity is rejected (Wald test statistic = 164.000, p = 0.000). Fourth, we employ Pesaran's cross-sectional dependence (CD)test [58], which is widely used for large panels (as is the case in this study) to check for the presence of CD within the panel. The test outcome indicates the presence of strong CD, suggesting that the null hypothesis of weak CD is rejected (CD statistic = 129.556, p = 0.000). Fifth, given the cross-sectional dependence and the study's large and unbalanced panel framework, we perform Maddala and Wu's [59] panel unit root tests by demeaning the data to remove the effects of CD [60–62]. Table 3 portrays the panel unit root test results. According to Choi [63], the inverse normal Z statistic offers the best trade-off between size and power. Furthermore, the modified inverse χ^2 statistic is appropriate for a large panel. Based on these two statistics, we find that the levels of *EXE* and *KNW* in the tests, with intercepts and time trends, have unit roots. This implies that the series is not stationary, but that the first difference of the variables is stationary.

Table 3. Panel unit root tests.

Statistic	Variable	With Trend		Without Trend	
		Level	1st-difference	Level	1st-difference
Inverse normal Z	*TFP*	0.857 (0.804)	–44.563 (0.000)	–15.086 (0.000)	–60.718 (0.000)
	EXE	0.863 (0.805)	–31.655 (0.000)	–2.900 (0.000)	–51.945 (0.000)
	KNW	6.120 (1.000)	–17.711 (0.000)	–11.973 (0.000)	–45.691 (0.000)
	COM	–16.280 (0.000)	–58.374 (0.000)	–27.604 (0.000)	–80.557 (0.000)
Modified inverse χ^2	*TFP*	11.912 (0.000)	79.428 (0.000)	24.448 (0.000)	109.316 (0.000)
	EXE	8.630 (0.000)	56.730 (0.000)	10.752 (0.000)	88.337 (0.000)
	KNW	6.228 (0.762)	46.302 (0.000)	22.733 (0.000)	69.354 (0.000)
	COM	24.360 (0.000)	104.605 (0.000)	34.978 (0.000)	153.851 (0.000)

Notes: Individual intercepts and time trends are included in the panel unit test. Automatic lag length selection (the Schwarz information criterion) is used. The null hypothesis for the test is a unit root, assuming an individual unit root process. *P*-values are in parentheses.

Sixth, the unit root test findings of non-stationarity for some variables indicate the possibility of examining the presence of long-term equilibrium among the variables by conducting Westerlund's [64] heterogeneous panel co-integration test, which allows for CD. The outcomes reported in Table 4 suggest no co-movement among *TFP*, *EXE*, *KNW*, and *COM* in both cases—with the constant and with the constant and the trend—and thus, the null hypothesis is not rejected in the absence of co-integration in the panel.

Table 4. Panel co-integration tests.

Statistic	With Trend			Without Trend		
	Value	Z-Value	Robust p-Value	Value	Z-Value	Robust p-Value
G_t	−2.001	27.996	0.850	−1.239	36.579	0.890
G_a	−5.705	42.389	0.800	−3.139	38.596	1.000
P_t	−95.106	−10.273	0.330	−78.372	−11.125	0.350
P_a	−9.727	11.112	0.370	−0.846	−8.032	0.380

Notes: To control for cross-sectional dependence, robust critical values are obtained through 100 bootstrap replications.

The results of the panel framework tests enable us to establish a dynamic panel vector autoregressive (PVAR) model in the first difference to test the relationship between the study variables. The existence of a first-order autocorrelation in the series signals that a dynamic model is appropriate. Hence, we employ a dependent variable in the previous period as an independent variable to control for autocorrelation. To control for cross-individual correlation, we create year dummy control variables following Sarafidis et al. [61] and Roodman [65] to improve the robustness of our results [66]. The presence of unit roots demonstrates that the first-differenced variables should be used to estimate an empirical model.

We therefore propose the PVAR model to test short-run dynamic relationships between exports and productivity. The PVAR model can be expressed as follows (Equation (2)):

$$\Delta Y_{i,t} = \zeta \Delta Y_{i,t-1} + \lambda \Delta X_{i,t-1} + \Delta \varepsilon_{i,t} + d_t, \tag{2}$$

where Δ is the first-difference operator, t is the period, $Y_{i,t}$ is a vector of the logs of the dependent variables, $X_{i,t}$ is a vector of the logs of the exogenous variables, $\varepsilon_{i,t}$ is a vector of idiosyncratic errors, and d_t is the time dummy. The vector of dependent and exogenous variables includes *TFP*, *EXE*, *KNW*, and *COM*.

Equation (2) has a simultaneity problem introduced by differencing, which occurs when the lagged exogenous variables correlate with the new differenced error term, and a heteroscedasticity problem that maintains a heterogeneous error with different firms in the panel. To solve these problems, we apply the panel generalized method of moments (GMM) with Helmert's procedure [67] following Love and Zicchino [68], whereby lagged regressors are used as instruments to estimate coefficients more consistently [69,70]. The GMM estimation framework is well suited for large panels (as is the case in this study) [71]. It is important to choose an optimal lag order in the PVAR and in the moment condition [72]. We use consistent moment and model selection criteria for the GMM model based on Hansen's [73] J statistic of overidentifying restriction, following Andrew and Lu [74]. Accordingly, we confirm that the one-lagged model is preferred based on Andrew and Lu's [74] three-model selection criteria: Modified Akaike, Bayesian, and Hannan-Quinn information criteria.

In the PVAR model, we assume that the vector of residuals ($\varepsilon_{i,t}$) is independent and identically distributed. However, this assumption is unrealistic, since the concrete variance–covariance matrix of the errors is unlikely to be diagonal. Therefore, to isolate the shocks to one of the VAR errors, we use the Cholesky decomposition method [75] to decompose the residuals so that they become orthogonal, and thereby compute orthogonalized impulse response functions (IRFs).

Table 5 depicts the estimation findings of the PVAR model. The findings of the GMM estimation, portrayed in Panel A of Table 5, indicate dynamic effects in all estimations; the current levels of ΔTFP_t, ΔEXE_t, ΔKNW_t, and ΔCOM_t are to some extent affected by their own levels in the previous period (ΔTFP_t, ΔEXE_t, ΔKNW_t, and ΔCOM_t, respectively). As shown in Panel A, four variables, including the one-lagged dependent variable, significantly affect *TFP* in the present period. The results from the panel causality tests in Panel B reveal a significant, positive, and bidirectional causal relationship between *TFP* and *EXE* or *KNW* at the 1% and 10% significance levels. The causality test results also indicate bidirectional causal relationships, which means that the variables are affected by an opposite sign between *TFP* and *COM* and between *KNW* and *COM*. *TFP* has a positive effect on *COM* at the 1% significance level, while *COM* has a negative effect on *TFP* at the 5% significance level. *KNW* has a positive effect on *COM* at the 1% significance level, while *COM* has a negative effect on *KNW* at the 1% significance level. We also find that *KNW* positively impacts *EXE* at the 1% significance level.

Table 5. Panel vector auto-regression results.

Panel A: GMM Estimation				
Independent Variables	**Dependent Variables**			
	ΔTFP_t	ΔEXE_t	ΔKNW_t	ΔCOM_t
ΔTFP_{t-1}	0.5496 (0.5978)***	2.8456 (0.0206)***	1.1219 (0.2450)***	1.9124 (0.3160)***
ΔEXE_{t-1}	0.0006 (0.0003)*	0.6826 (0.0108)***	−0.0012 (0.0018)	0.0019 (0.0026)
ΔKNW_{t-1}	0.0077 (0.0027)***	0.6016 (0.0015)***	0.9809 (0.0104)***	0.1130 (0.0213)***
ΔCOM_{t-1}	−0.0032 (0.0014)**	−0.0201 (0.0286)	−0.0133 (0.0052)***	0.1579 (0.0118)***
Panel B: Statistical Values for Short-Run Causality Tests				
Independent Variables	**Dependent Variable**			
	ΔTFP	ΔEXE	ΔKNW	ΔCOM
ΔTFP	-	7.774***	20.961***	36.622***
ΔEXE	2.592*	-	1.048	0.510
ΔKNW	7.717***	66.788***	-	27.940***
ΔCOM	4.703**	0.495	6.404 ***	-

Notes: Panel A contains the results of the panel vector autoregressive (VAR) model. Time dummies are not reported. Panel B depicts χ^2 statistics. In both panels, ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. Heteroscedasticity and serial correlation robust standard errors are in parentheses.

The dynamic causal relationships, as determined from the causality tests, are outlined in a causal loop diagram in Figure 1.

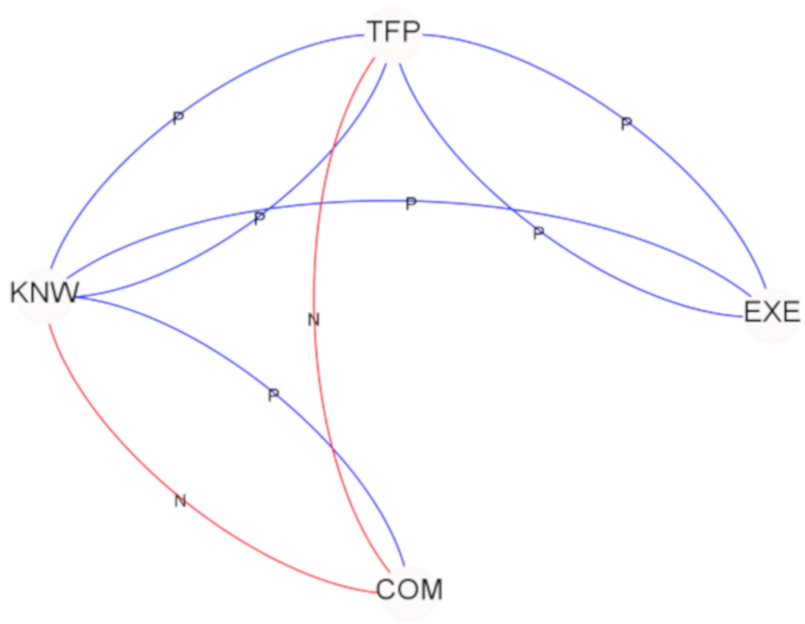

Figure 1. TFP, EXE, KNW, and COM denote total factor productivity, export, knowledge assets, and industry competition, respectively. Casual loop diagram. P (in blue) and N (in red) stand for positive and negative casual relationships, respectively. The directions are set to clockwise.

Following the estimations of the PVAR model, we confirm that the PVAR model is stable (the results are available upon request from the authors). Then, we calculate orthogonalized IRFs via the Cholesky factorization scheme. We note the response of one variable to another variable to zero in the first period due to the ordering (the same ordering as in the PVAR specification). Figure 2 plots the responses of *TFP*, *EXE*, *KNW*, and *COM* to a shock in the one-lag PVAR model. The findings indicate a virtuous cycle between *TFP*, *EXE*, and *KNW*. A positive shock in *EXE* leads to a statistically significant, positive response of *TFP*, and vice versa, a statistically significant, positive response of *EXE* to positive shock in *TFP*. Meanwhile, a positive shock in *KNW* produces a statistically significant, positive response of *EXE* and *TFP*, and vice versa, a statistically significant, positive response. As depicted in Figure 2, an export shock of one standard deviation results in an increase of 0.003% in *TFP* for two years, then an increase of 0.002% for three years, followed by an increase of 0.001% for 10 years. A knowledge assets shock of one standard deviation generates an increase of 0.007% on average in *TFP* for six years, and then an increase of 0.009% after six years. Furthermore, a knowledge assets shock of one standard deviation triggers an increase of approximately 0.5% on average in exports for four years, and then an increase of approximately 0.9% after four years. However, a positive shock in industry competition leads to statistically significant, negative changes in exports and knowledge assets.

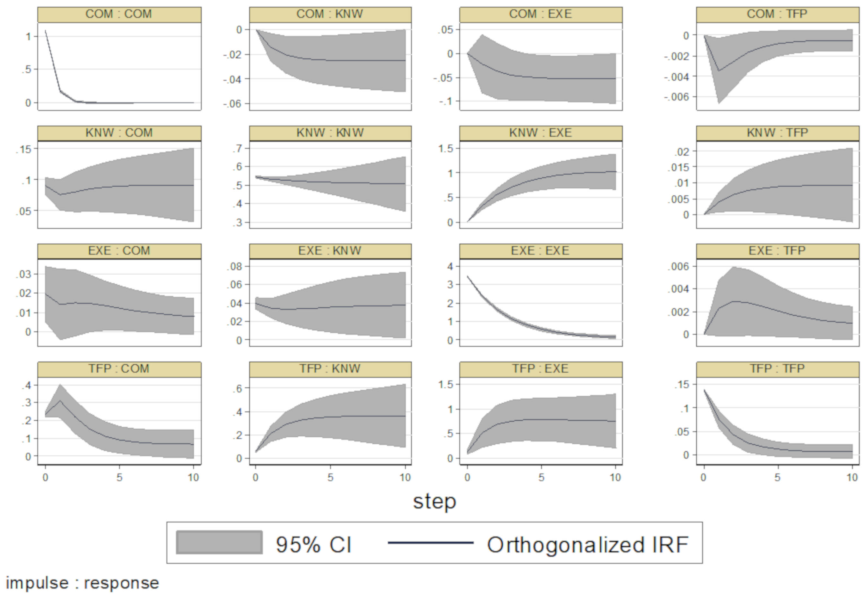

Figure 2. Impulse response functions (IRFs) for the panel vector autoregressive (PVAR) results. CI denotes confidence intervals.

5. Discussion

Our main outcomes and implications are as follows. First, although prior results are mixed, our study follows Bernard and Jensen [1], Bernard and Wagner [2], Bernard et al. [3], Wagner [4], and Bernard et al. [5] in providing evidence of the existence of an LBE effect (i.e., productivity enhancement from exporting). This demonstrates that firms' exporting has a positive effect on their *TFP*. The results indicate that a 1% increase in exports boosts an organization's *TFP* by 0.0006%. These outcomes imply that an enterprise can benefit from export activities by learning and amassing the resources engendered through entry into export markets (e.g., advanced technologies, best practices, and valuable know-how and information). Considering that over 44% of South Korea's gross domestic product (GDP) has relied on exports since 2000, productivity enhancement from exports is pivotal for income growth, which can raise South Korean living standards in the long term. The significant learning gained through exporting signals that the government should efficiently and effectively implement policies designed to support firms' export participation, as well as export-promotion services aimed at reducing information asymmetry and the fixed costs linked to exporting (e.g., training in the export process, specific information services for foreign markets, participation in international fairs, and export promotion programs), especially for non-exporting firms and less-mature exporting firms [76,77]. Our study reveals the underlying mechanisms of benefits gained from exports, indicating that *TFP* can be augmented by interacting with exports and knowledge assets. However, the government should keep in mind that efficient and effective implementation of policies and services to aid companies' export participation largely depends on a comprehensive understanding of such foundational mechanisms.

Second, we find that firms' *TFP* is significantly positively affected by their knowledge assets. Productivity is a key export factor, as asserted by trade theories, and is driven by continuous innovation creation. The accumulation and use of knowledge assets are closely tied to international business. The international business environment requires companies to constantly accrue, renew, and utilize their knowledge assets. As Swart and Kinnie [78] argue, this accumulation, renewal, and use of knowledge assets can be understood in terms of an organization's ability to learn, which means that organizational learning is a dynamic process. Hence, our results indicate that enterprises should explore new learning opportunities both internally and externally, and that the government should carry out policy instruments to support firms' organizational learning, thereby fostering competitiveness in a rapidly changing global market. According to Weerawardena et al. [76], market-focused learning that enables firms to acquire, disseminate, unlearn, and use market information for organizational change improves the speed and effectiveness of their responses to business opportunities and threats, which are central elements of industry dynamism. A more industry-dynamic, competitive setting calls for faster, more systematic, and successful responses to such opportunities and threats. A competitive atmosphere requires firms to create novel innovative products and services to succeed [77]. Thus, when industry competition is fierce, companies actively promote organizational learning by better utilizing market-focused knowledge to stay ahead of competitors and survive in the fiercely competitive milieu. Therefore, various policy measures for promoting a competitive environment should be used to encourage firms' proactive learning.

We can consider the above discussion based on our study's finding of a positive effect of knowledge assets on exports. This finding indicates a dynamic path for export growth through productivity enhancement, resulting from learning-based innovations centered on continuous accumulation, renewal, and utilization of knowledge assets. Heterogeneous trade theory also claims that competition induces firms' productivity growth. The formation of a competitive atmosphere to boost firms' proactive learning is essential for export growth. Despite the importance of a competitive environment, we show that industry competition has a negative effect on *TFP* and knowledge assets. These outcomes do not necessarily signal that industry competition is unimportant for advancing export growth by improving productivity; rather, the takeaway is that a competitive setting is not yet sufficiently developed to drive productivity and export growth. Competition increases knowledge asset efficiency [79]. In a competitive milieu, knowledge assets, as a predominant resource, foster their usage in combination with other production inputs [80] or tangibles. Thus, in the context of heterogeneous firm trade theory, our results suggest that the government should devise policies to encourage competition across firms. This will lead to reallocation of production factors to more competent enterprises and the realization of an aggregate productivity gain in society.

Third, our study reveals a dynamic path dependence in terms of *TFP*; this means that current productivity can be an input source for future productivity (0.549% in *TFP*). Hence, the value of productivity in the current period depends on its value in the previous period at the 1% significance level, and there is a time lag between productivity, exports, and industry dynamics. These findings signify that the time lag should be taken into account when developing and carrying out policy measures to stimulate firms' productivity, and that it takes time for companies to realize LBE. In addition, there is a path dependence in knowledge assets, exports, and industry competition: Their present value depends on their previous value. Taking into account diverse causal loops between *TFP* and *EXE*, *TNW*, and *COM* to examine the LBE effect, persistent efforts are required to increase exports and knowledge assets, as well as to aid industry competition.

6. Conclusions

We empirically explore the effect of knowledge assets on the relationship between exports and productivity using panel data for South Korean manufacturing firms listed in the South Korean stock market from 1991 to 2018. We establish a dynamic PVAR model in the first difference that considers key data characteristics. We estimated the model using the GMM estimator. We conducted a post-estimation test, Granger causality test and impulse response test. Our study expands the understanding of the role of knowledge assets in the LBE effect for firms in the short term, especially when organizations face global competitive and knowledge-based environments. However, the study has several limitations. Our results are specific to South Korea, and the impacts of knowledge assets on productivity may vary across countries. The feedback loops between productivity and other factors (e.g., knowledge assets, exports, industry competition) at the firm level in each country's manufacturing sector should be thoroughly taken into account, especially regarding certain elements and the situational context facing each nation. Furthermore, we control for CD (inter-firm spillovers) by creating year dummy variables based on Sarafidis et al. [61] and Roodman [65] due to data unavailability. Inter-firm spillovers are affected by similarities among technologies [81] and products [82]. Thus, future studies should control for cross-dependence more systematically.

Author Contributions: H.-J.K. and B.S. designed the study and established the theoretical model. B.S. estimated the empirical model. H.-J.K. and B.S. discussed the findings. All authors have read and approved the final manuscript.

Funding: This work was supported by a 2019 research grant from Kyonggi University (2019-043).

Acknowledgments: We deeply appreciate the editors and three anonymous reviewers who provided constructive criticism and suggestions, which helped us improve the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bernard, A.B.; Jensen, J.B. Exporters, jobs, and wages in U.S. manufacturing: 1976–1987. In *Brookings Papers on Economic Activity. Microeconomics*; Brookings Institution Press: Washington, DC, USA, 1995; pp. 67–119. [CrossRef]
2. Bernard, A.B.; Wagner, J. Exports and successes in German manufacturing. *Rev. World Econ.* **1997**, *133*, 134–157.
3. Bernard, A.B.; Jensen, J.B.; Redding, S.J.; Schott, P.K. Firms in international trade. *J. Econ. Perspect.* **2007**, *21*, 105–130. [CrossRef]
4. Wagner, J. Exports and productivity: A survey of the evidence from firm-level data. *World Econ.* **2007**, *30*, 60–80. [CrossRef]
5. Bernard, A.B.; Jensen, J.B.; Redding, S.J.; Schott, P.K. The empirics of firm heterogeneity and international trade. *Annu. Rev. Econ.* **2012**, *4*, 283–313. [CrossRef]
6. Araújo, B.C.; Salerno, M.S. Technological strategies and learning-by-exporting: The case of Brazilian manufacturing firms, 2006–2008. *Int. Bus. Rev.* **2015**, *24*, 725–738. [CrossRef]
7. Aw, B.Y.; Robert, M.J.; Xu, D.Y. R&D investments, exporting, and the evolution of firm productivity. *Am. Econ. Rev.* **2008**, *98*, 451–456.
8. Lindstrand, A.; Eriksson, K.; Sharma, D.D. The perceived usefulness of knowledge supplied by foreign client networks. *Int. Bus. Rev.* **2009**, *18*, 26–37. [CrossRef]
9. Castellani, D. Export behavior and productivity growth: Evidence from Italian manufacturing firms. *Rev. World Econ.* **2002**, *138*, 605–628. [CrossRef]
10. Damijan, J.; Kostevc, C. Learning by exporting: Continuous productivity improvements or capacity utilization effects? Evidence from Slovenian firms. *Rev. World Econ.* **2006**, *142*, 599–614. [CrossRef]
11. Ciuriak, D.; Lapham, B.; Wolfe, R.; Collins-Williams, T.; Curtis, J. Firms in international trade: Trade policy implications of the new trade theory. *Glob. Policy* **2015**, *6*, 130–140. [CrossRef]

12. Wang, W.; Ma, H. Export strategy, export intensity and learning: Integrating the resource perspective and institutional perspective. *J. World Bus.* **2018**, *53*, 581–592. [CrossRef]
13. Silva, A.; Afonso, O.; Africano, A.P. Learning-by-exporting: What we know and what we would like to know. *Int. Trade J.* **2012**, *26*, 255–288. [CrossRef]
14. Crespi, G.; Coouolo, C.; Haskel, J. Productivity, exporting and the learning by exporting hypothesis: Direct evidence from UK firms. *Can. J. Econ.* **2008**, *41*, 619–638. [CrossRef]
15. Haidar, J.I. Trade and productivity: Self-selection or learning-by-exporting in India. *Econ. Model.* **2012**, *29*, 1766–1773. [CrossRef]
16. Sharma, C.; Mishra, R.K. International trade and performance of firms: Unraveling export, import and production puzzle. *Q. Rev. Econ. Financ.* **2015**, *57*, 61–74. [CrossRef]
17. Chen, T.; Chen, X.; Wang, C.; Xiang, X. Export behavior and firm innovation: New method and evidence. *Econ. Lett.* **2018**, *170*, 76–78. [CrossRef]
18. McDowell, W.C.; Peake, W.O.; Coder, L.; Harris, M.L. Building small firm performance through intellectual capital development: Exploring innovation as the "black box". *J. Bus. Res.* **2018**, *88*, 321–327. [CrossRef]
19. Agostini, L.; Nosella, A.; Filippini, R. Does intellectual capital allow improving innovation performance? A quantitative analysis in the SME context. *J. Intellect. Cap.* **2017**, *18*, 400–418. [CrossRef]
20. Chen, F.-C.; Liu, Z.J.; Kewh, Q.L. Intellectual capital and productivity of Malaysian general insurers. *Econ. Model.* **2014**, *36*, 413–420. [CrossRef]
21. Oppong, G.; Pattanayak, J.; Irfan, M. Impact of intellectual capital on productivity of insurance companies in Ghana: A panel data analysis with system GMM estimation. *J. Intellect. Cap.* **2019**, *20*, 763–783. [CrossRef]
22. Wignaraja, G. Innovation, learning, and exporting in China: Does R&D or a technology index matter? *J. Asian Econ.* **2012**, *23*, 224–233.
23. Coad, A.; Segarra, A.; Teruel, M. Innovation and firm growth: Does firm age play a role? *Res. Policy* **2016**, *45*, 387–400. [CrossRef]
24. Kolb, D.A. *Experiential Learning: Experience as the Source of Learning and Development*; Prentice-Hall: Englewood Cliffs, NJ, USA, 1984.
25. Kim, D.H. The link between individual and organizational learning. *MIT Sloan Manag. Rev.* **1993**, *35*, 37–50.
26. Eriksson, K.; Johanson, J.; Majkgard, A.; Sharma, D.D. Effect of variation on knowledge accumulation in the internationalization process. *Int. Stud. Manag. Organ.* **2000**, *30*, 26–44. [CrossRef]
27. Pellegrino, J.M.; McNaughton, R.B. Beyond learning by experience: The case of alternative learning process by incrementally and rapidly internationalizing SMEs. *Int. Bus. Rev.* **2017**, *26*, 614–627. [CrossRef]
28. Johanson, J.; Vahlne, J.E. The internationalization process of the firm—A model of knowledge development and increasing foreign market commitment. *J. Int. Bus. Stud.* **1977**, *8*, 23–32. [CrossRef]
29. Casillas, J.C.; Acedoa, F.J.; Barberob, J.L. Learning, unlearning and internationalisation: Evidence from the pre-export phase. *Int. J. Inf. Manag.* **2010**, *30*, 162–173. [CrossRef]
30. Cohen, W.M.; Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, *35*, 128–152. [CrossRef]
31. Kianto, A.; Sáenz, J.; Aramburu, N. Knowledge-based human resource management practices, intellectual capital and innovation. *J. Bus. Res.* **2017**, *18*, 11–20. [CrossRef]
32. Zambon, S.; Marzo, G. *Visualising Intangibles: Reporting in the Knowledge Economy*; Ashgate Publishing: Aldershot, UK, 2007.
33. Pulic, A. Intellectual capital–Does it create or destroy value? *Meas. Bus. Excell.* **2004**, *8*, 62–68. [CrossRef]
34. Costa, R. Assessing intellectual capital efficiency and productivity: An application to the Italian yacht manufacturing sector. *Expert Syst. Appl.* **2012**, *39*, 7255–7261. [CrossRef]
35. Marrocu, E.; Paci, R.; Pontis, M. Intangible capital and firms' productivity. *Ind. Corp. Chang.* **2011**, *21*, 377–402. [CrossRef]
36. Bontis, N.; Keow, W.C.C.; Richardson, S. Intellectual capital and business performance in Malaysian industries. *J. Intellect. Cap.* **2000**, *1*, 85–100. [CrossRef]
37. Bakhsha, A.; Afrazeh, A.; Esfahanipour, A. Identifying the variables of intellectual capital and its dimensions with the approach of structural equations in the educational technology of Iran. *EURASIS J. Math. Sci. Technol. Educ.* **2017**, *14*, 1663–1682.
38. Ryu, T.-G.; Lim, S.-J.; Kim, H.-J. *Studies on Intellectual Property and Economic Development: Estimation of Economic Value of Korean Intellectual Capital and Patents*; Korea Institute of Intellectual Property: Seoul, Korea, 2012.

39. Hsu, Y.-H.; Fang, W. Intellectual capital and new product development performance: The mediating role of organizational learning capability. *Technol. Forecast. Soc. Chang.* **2009**, *76*, 664–677. [CrossRef]
40. Roos, J.; Roos, G.; Edvinsson, L.; Dragonetti, N.C. *Intellectual Capital: Navigating in the New Business Landscape*; Macmillan: New York, NY, USA, 1997.
41. Chen, F.-C.; Shu, Z.; Xie, H. Measuring intellectual capital: A new model and empirical study. *J. Intellect. Cap.* **2004**, *l5*, 195–212. [CrossRef]
42. Asonitis, S.; Kostagiolas, P.A. An analytic hierarchy approach for intellectual capital: Evidence for the Greek central public libraries. *Libr. Manag.* **2010**, *31*, 145–161. [CrossRef]
43. Sivadas, E.; Dwyer, R.F. An examination of organizational factors influencing new product success in internal and alliance-based processes. *J. Mark.* **2000**, *64*, 31–49. [CrossRef]
44. Glynn, M.S. Primer in B2B brand-building strategies with a reader practicum. *J. Bus. Res.* **2012**, *65*, 666–675. [CrossRef]
45. Nadeau, M.-C.; Kar, A.; Roth, R.; Kirchain, R. A dynamic process-based cost modeling approach to understand learning effects in manufacturing. *Int. J. Prod. Econ.* **2010**, *128*, 223–234. [CrossRef]
46. An, G.; Iyigun, M.F. The export technology content, learning by doing and specialization in foreign trade. *J. Int. Econ.* **2004**, *64*, 465–483. [CrossRef]
47. Casillas, J.C.; Moreno, A.M.; Acedo, F.J. Path dependence view of export behavior: A relationship between static patterns and dynamic configurations. *Int. Bus. Rev.* **2012**, *21*, 465–479. [CrossRef]
48. Bernard, A.B.; Jensen, J.B. Exceptional exporter performance: Cause, effect, or both? *J. Int. Econ.* **1999**, *47*, 1–25. [CrossRef]
49. Monreal-Pérez, J.; Aragón-Sánchez, A.; Sánchez-Marín, G.A. A longitudinal study of the relationship between export activity and innovation in the Spanish firm: The moderating role of productivity. *Int. Bus. Rev.* **2012**, *21*, 862–877. [CrossRef]
50. Levinsohn, J.; Petrin, A. Estimating production functions using inputs to control for unobservables. *Rev. Econ. Stud.* **2003**, *70*, 317–342. [CrossRef]
51. Grossman, G.M.; Helpman, E. *Innovation and Growth in the Global Economy*; MIT Press: Cambridge, MA, USA, 1991.
52. Salomon, R.; Jin, B. Do leading or lagging firms learn more from exporting? *Strateg. Manag. J.* **2010**, *31*, 1088–1113. [CrossRef]
53. Lerner, A.P. The concept of monopoly and the measurement of monopoly power. *Rev. Econ. Stud.* **1934**, *1*, 157–175. [CrossRef]
54. Sung, B.; Park, S.-D.; Song, W.-Y. How foreign direct investment affects CO_2 emission levels in the Chinese manufacturing industry: Evidence from panel data. *Econ. Syst.* **2018**, *43*, 320–331. [CrossRef]
55. Del Gatto, M.; Mion, G.; Ottaviano, G.I.P. Trade integration, firm selection and the costs of non-Europe. In *CEPR Discussion Paper*; No. 5730; National Bureau of Economic Research: Cambridge, MA, USA, 2006.
56. Melitz, M.; Ottaviano, G.I.P. Market size, trade and productivity. In *NBER Working Paper*; No. 11393; National Bureau of Economic Research: Cambridge, MA, USA, 2005.
57. Wooldridge, J.M. *Econometric Analysis of Cross Section and Panel Data*; MIT Press: Cambridge, MA, USA, 2002.
58. Pesaran, M.H. Testing weak cross-sectional dependence in large panels. *J. Econ. Rev.* **2015**, *34*, 1089–1117. [CrossRef]
59. Maddala, G.S.; Wu, S.A. A comparative study of unit root tests with panel data and a new simple test. *Oxf. Bull. Econ. Stat.* **1999**, *61*, 631–652. [CrossRef]
60. Raponi, V.; Robotti, C.; Zaffaroni, P. Testing beta-pricing models using large cross-sections. *Rev. Financ. Stud.* **2019**. [CrossRef]
61. Sarafidis, V.; Yamagata, T.; Robertson, D. A test for cross section dependence for a linear dynamic panel model with regressors. *J. Econom.* **2009**, *148*, 149–161. [CrossRef]
62. Solberger, M. Demeaning the data in panel-cointegration models to control for cross-sectional dependencies. *Econ. Lett.* **2011**, *110*, 252–254. [CrossRef]
63. Cho, I. Unit root tests for panel data. *J. Int. Money Financ.* **2001**, *20*, 249–272. [CrossRef]
64. Westerlund, J. Testing for error correction in panel data. *Oxf. Bull. Econ. Stat.* **2007**, *34*, 63–87. [CrossRef]
65. Roodman, D. How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata J.* **2009**, *9*, 86–136. [CrossRef]

66. D'Amato, A.; Mazzanti, M.; Nicolli, F. Waste and organized crime in regional environments: How waste tariffs and the Mafia affect waste management and disposal. *Resour. Energy Econ.* **2015**, *41*, 185–201. [CrossRef]
67. Arellano, M.; Bover, O. Another look at the instrumental variable estimation of error-component model. *J. Econom.* **1995**, *68*, 29–51. [CrossRef]
68. Love, I.; Zicchino, L. Financial development and dynamic investment behavior: Evidence from panel VAR. *Q. Rev. Econ. Financ.* **2006**, *46*, 190–210. [CrossRef]
69. Gnimassoun, B.; Mignon, V. How do macroeconomic imbalances interest? Evidence from a panel var analysis. *Macroecon. Dyn.* **2016**, *20*, 1717–1741. [CrossRef]
70. Comunale, M. *A Panel VAR Analysis of Macro-Financial Imbalances in the EU*; Working Paper Series 2016; European Central Bank: Frankfurt am Main, Germany, 2017.
71. Adraov, A. Dynamic interactions between financial and macroeconomics imbalances: A panel VAR analysis. In *Working Paper 162*; The Vienna Institute for International Economic Studies: Vienna, Austria, 2019.
72. Abrigo, M.R.M.; Love, I. Estimation of panel vector autoregression in Stata. *Stata J.* **2016**, *16*, 778–804. [CrossRef]
73. Hansen, J. Large sample properties of generalized method of moments estimator. *Econometrica* **1982**, *50*, 1029–1054. [CrossRef]
74. Andrews, D.W.K.; Lu, B. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *J. Econom.* **2001**, *101*, 123–164. [CrossRef]
75. Sims, C.A. Macroeconomics and reality. *Econometrica* **1980**, *48*, 1–48. [CrossRef]
76. Weerawardena, J.; O'Cass, A.; Julian, C. Does industry matter? Examining the role of industry structure and organizational learning in innovation and brand performance. *J. Bus. Res.* **2006**, *59*, 37–45. [CrossRef]
77. Durana, P.; Valaskova, K.; Vagner, L.; Zadnanova, S.; Podhorska, I.; Siekelova, A. Disclosure of strategic managers' factotum: Behavioral incentives of innovative business. *Int. J. Financ. Stud.* **2020**, *8*, 17. [CrossRef]
78. Swart, J.; Kinnie, N. Organisational learning, knowledge assets and HR practices in professional service firms. *Hum. Resour. Manag. J.* **2010**, *20*, 64–79. [CrossRef]
79. Tripathy, T.; Sahoo, D.; Kesharwani, A.; Mishra, A.K. Competition, intellectual capital efficiency and firms' performance outcome in India: A structural equation modelling. *Int. J. Learn. Intellect. Cap.* **2016**, *13*, 72–95. [CrossRef]
80. Montresor, S.; Perani, G.; Vezzani, A. How do companies "perceive" their intangible? New statistical evidence from the INNOBAROMETER. In *IRIMA Workpackage 2, JRC Scientific and Technological Reports*; Joint Research Centre: Brussels, Belgium, 2013.
81. Pender, M. *Entrepreneurial Competition and Industrial Location*; Edward Elgar: Cheltenham, UK, 2001.
82. Gong, B. Total-factor spillovers, similarities, and competitions in the petroleum industry. *Energy Econ.* **2018**, *73*, 228–238. [CrossRef]