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ÖZGÜN ARAŞTIRMA

Superimposing Space onto the Relationship between Financial Development and Economic Growth

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Abstract

We investigate the relationship between financial development (FD) and economic growth (EG) for a selected sample of 20 emerging market economies by adopting a dynamic spatial modelling framework with common factors. Annual data for the period 1996-2018 is used. Empirical findings suggest that FD affects EG negatively. Furthermore, there are negative spillovers on the EG rates of the neighboring countries which are generated by the financial sector improvements in any single emerging country. This is a striking finding that it questions the old argument that financial sector or financial market development leads always to favorable effects on economic performance. The policy suggestion that follows is that the policy makers in the sampled countries should keep the financial sectors under control by regulations so as to stabilize their EG rates. Besides, they should design economic policy measures to protect their economic performances from the negative spillovers transmitted from the neighboring emerging countries.

Keywords: *Financial development, economic growth, spatial dependence, common factors*
Jel classification: *C23, E44, F41, G15*

Finansal Gelişme ve Ekonomik Büyüme İlişkisine Mekân Eklenmesi

Özet

Bu çalışma, seçilmiş 20 yükselen piyasa ekonomisinde finansal gelişme (FD) ile ekonomik büyüme (EG) arasındaki ilişkiyi, 1996-2018 dönemini kapsayan yıllık veriler kullanılarak yürütülen ortak faktörlü dinamik mekansal modelleme aracılığıyla araştırmaktadır. Ampirik analizlerden elde edilen bulgulara göre; FD, EG'yi negatif yönde etkilemektedir. Buna ek olarak, komşu ülkelerin EG'leri üzerinde, herhangi bir yükselen piyasa ekonomisindeki finans sektörü gelişmelerinin meydana getirdiği negatif bulaşma etkileri tespit edilmiştir. Bu önemli bulgu, finans sektörü veya finansal piyasa gelişiminin her zaman ekonomik performans üzerinde olumlu etkilere neden olacağı şeklindeki eski argümanı sorgulamaktadır. Bu sonuçların ışığında elde edilen politika önerisine göre, örneklemdeki ülkelerin politika yapıcılarının EG oranlarını stabilize etmek için finans sektörlerini düzenlemeler yardımıyla kontrol altında tutmaları gerekmektedir. Ayrıca, kendi ekonomik performanslarını, gelişmekte olan komşu ülkelerden gelen negatif bulaşmalardan korumak amacıyla ekonomi politikası önlemleri dizayn etmeleri de gerekmektedir.

Anahtar kelimeler: *Finansal gelişme, ekonomik büyüme, mekansal bağımlılık, ortak faktörler*
Jel sınıflandırması: *C23, E44, F41, G15*

1. INTRODUCTION

Debate on the relationship between financial development (FD) and economic growth (EG) begins with Schumpeter's (1911) seminal work and it has been catching the eye of the policy makers, academics as well as layperson ever since. Schumpeter (1911) puts forward that FD affects economic activity positively on the grounds that the existence of well-functioning banks and financial markets in an economy brings about the efficient allocation of productive funds which in turn enhances EG. This argument found widespread support before long by the influential works of Gurley and Shaw (1955), Goldsmith (1969), McKinnon (1973), and Shaw (1973).

Though the initial contributions point to the significant role of financial intermediation in accelerating EG, recent empirical evidence is not clear-cut. Studies in the related literature

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can be classified into three groups in terms of their empirical methodology: cross-sectional, time series, and panel data analyses. Cross-sectional papers generally favor banking system and/or stock market development as a stimulus for economic activity (see, King and Levine, 1993; Levine and Zervos, 1996; Azman-Saini et al., 2010, among others). Empirical works that employ time series or panel data models report mixed results even for similar countries or country groups. Some prominent papers among others are as follows: Demetriades (1996), Levine (1999), Arestis et al. (2001), Bumann et al. (2013), Caporale et al. (2015), Samargandi et al. (2015), Shahbaz et al. (2015), Kandil et al. (2017), and most recently Asteriou and Spanos (2019), who conducted a panel data analysis for 26 EU countries and found conflicting evidence for the before- and after- 2008 crisis periods.

The present study, as far as we are concerned, is distinguished from the vast number of earlier works in the sense that the finance-growth nexus is evaluated by a spatial econometric point of view. More specifically, we employed dynamic spatial panel data models with different forms of common factors and used annual data for the period 1996-2018 to examine the relationship between FD and EG in the selected 20 emerging market economies[3]. The novelty of the empirical findings from this study can be attributed to the following properties: *(i)* we employ a weight matrix that shows the spatial connectivity among the neighboring nations, the elements of which are made up of inverse of the geographical distance among the sampled countries' capital cities[4]. *(ii)* we also employ common factors following the recent advances in spatial modelling in order to distinguish between weak and strong cross-sectional dependence[5]. *(iii)* we estimate the short- and long-run direct and indirect (or spatial spillover) effects of the independent variable on the dependent variable, i.e. FD and EG, respectively. The rest of the study is organized as follows: second section illustrates the data and depicts the empirical methodology and the econometric model. Third section discusses the findings and finally, fourth section concludes.

2. DATA AND ECONOMETRIC METHODOLOGY

2.1. Data

This paper explores the relationship between FD and EG in a selected sample of 20 emerging market economies by employing dynamic spatial panel data models with different forms of common factors. Annual data that covers the period 1996-2018 is used. FD and EG series are collected from IMF's financial development index and World Bank's world development indicators (online) databases, respectively. The data for the distance among the capitals of the sampled countries is obtained from the online database of CEPII (Centre d'Etudes Prospectives et d'Informations Internationales). Descriptive statistics for the sample is illustrated in Table 1. FD and EG series for the sampled countries is depicted below by Figure 1 and Figure 2, respectively[6].

[3] These selected countries which are determined depending on data availability are as follows: Brazil, Bulgaria, Chile, Hong Kong, China, Croatia, Czech Republic, Hungary, Indonesia, Republic of Korea, Malaysia, Mexico, Philippines, Poland, Romania, Russian Federation, Slovak Republic, South Africa, Thailand, and Turkey

[4] Other weight matrices that reflect different forms of spatial connections among the neighbours can be specified in a further study. Construction of the inverse distance weight matrix employed here is explained in details in the next section.

[5] The literature on the dynamic spatial modelling strategy which incorporates common factors into the models is growing very rapidly. To name some of the leading and most recent ones: Halleck-Vega and Elhorst (2016), Shi and Lee (2017) and (2018), Ciccarelli and Elhorst (2018), Elhorst et al. (2020) and Servén and Abate (2020).

[6] To gain space, graphics and descriptive statistics for individual countries regarding FD and EG are shown in the Appendix in Figure A1 and Figure A2 and in Table A1 and Table A2, respectively.

Table 1: Descriptive statistics for the selected 20 emerging market economies

	EG	FD
Mean	0.035340	0.462148
Median	0.039350	0.448480
Maximum	0.142314	0.852783
Minimum	-0.141928	0.128244
Std. Dev.	0.035618	0.151127
Skewness	-0.958094	0.539532
Kurtosis	5.833752	2.921395
Observations	460	460

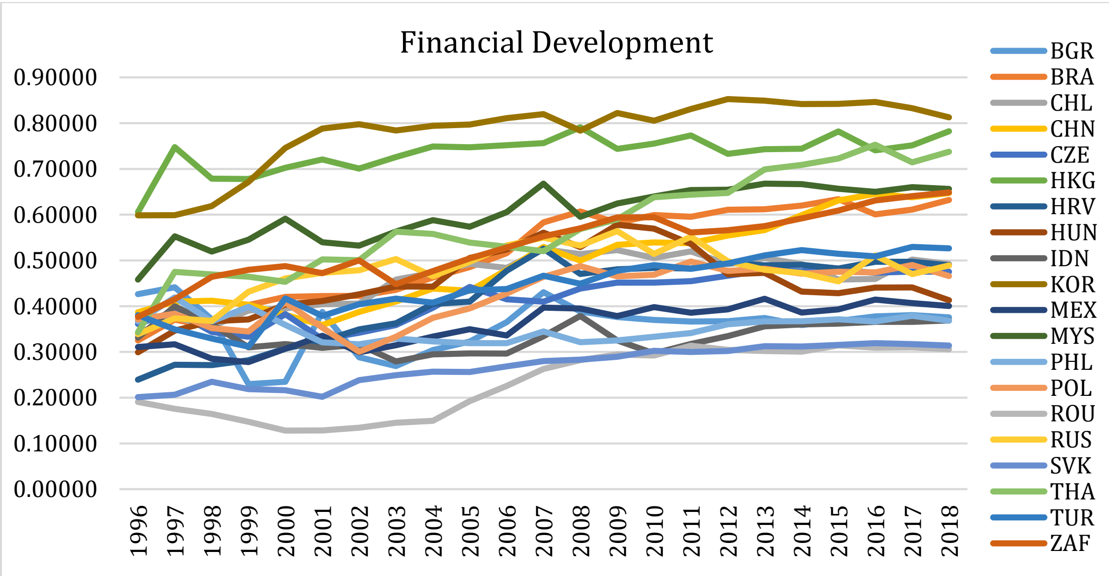

Figure 1: FD series for the sampled countries (combined)

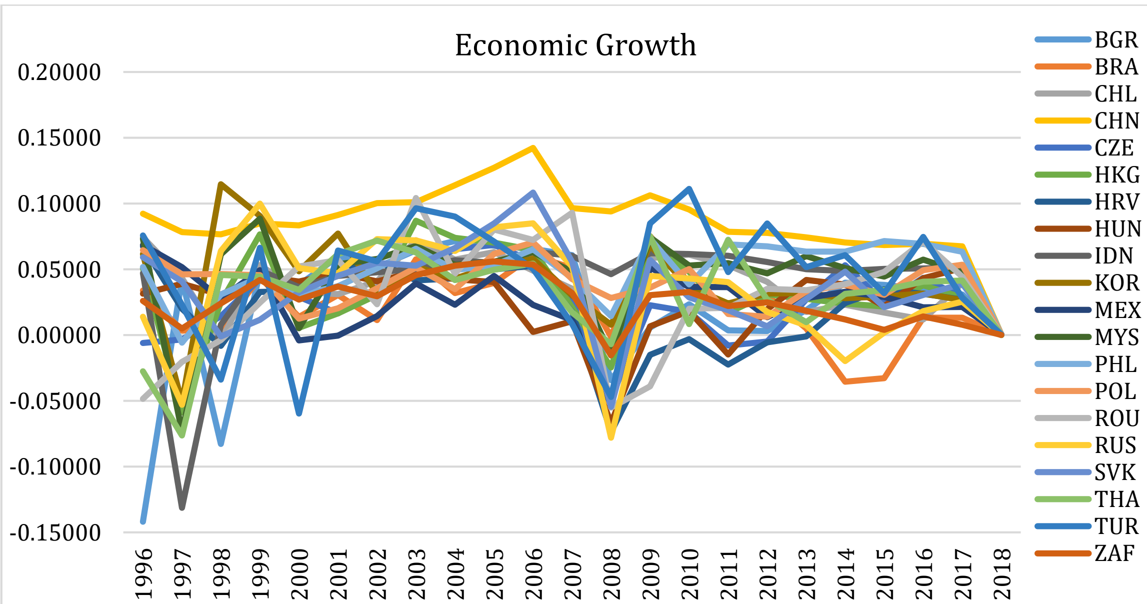

Figure 2: EG series for the sampled countries (combined)

2.2. Econometric Methodology

In this study, different from the previous papers, we add space into the relationship between FD and EG by adopting a dynamic spatial modelling methodology which also includes different forms of common factors. We estimated the dynamic spatial Durbin model (SDM) illustrated in Eq. (1):

$$EG_{it} = \tau EG_{it-1} + \delta \sum_{j=1}^{N} w_{ij} EG_{jt} + \eta \sum_{j=1}^{N} w_{ij} EG_{jt-1} + \theta \sum_{j=1}^{N} w_{ij} FD_{jt} + \beta FD_{it} + \Gamma \overline{EG}_{t-1} + \mu + \xi_t \iota_N + v_{it} \quad (1)$$

where $\mathrm{EG_{it-1}}$, $\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{w_{ij}EG_{jt}}$, and $\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{w_{ij}EG_{jt-1}}$ represent temporal, spatial, and temporal-spatial (spatiotemporal) lag of the dependent variable, respectively. The coefficients τ, δ, and η are called as the serial, spatial, and spatiotemporal autoregressive parameters, respectively. $\mathrm{w_{ij}}$ shows the $\mathrm{ij^{th}}$ element of the spatial weight matrix w, which has NxN dimensions. The component $\sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{w_{ij}FD_{jt}}$ stands for the spatial lag of the independent variable. $\overline{\mathrm{EG}}_{\mathrm{t-1}}$ is the common factor which is identical to the cross-sectional average of the dependent variable at time $\mathrm{t-1}$. Γ indicates the $Nx1$ matrix of unit-specific parameters associated with the common factor. μ and $\mathrm{\xi_t \iota_N}$ imply respectively the spatial and time period fixed effects which is common for all cross-section units. $\mathrm{\iota_N}$ is a $Nx1$ vector made up of ones. $Nx1$ vector $\mathrm{v_{it}}$ includes i.i.d. disturbances with zero mean and finite variance σ^2.

We also estimated the spatial autoregressive (SAR) model which is obtained by dropping the spatial lag of the explanatory variable from SDM, meaning that the latter nests the first. This estimation methodology serves as a robustness check since it allows us to compare the estimation results from two dynamic spatial models that comprise different interaction components. Specification of the weight matrix is of vital importance in spatial analysis. An inverse distance weight matrix, which is computed as follows is employed: $w_{ij} = 1/d_{ij}$, where d_{ij} symbolizes the geographical distance between two neighboring countries', i.e. i and j, capital cities.

Elhorst (2014), Ciccarelli and Elhorst (2018), and Elhorst, Madre, and Pirotte (2020) put that the long-term direct and indirect (spatial spillover) effects are distinguished by Eq. (2). The column sums of the off-diagonal elements of Eq. (2) imply spillover effects which shows the impact of a change in FD of a particular nation on the EG rates of all other neighboring nations. The average of the diagonal elements of Eq. (2) represents the direct effect which uncovers the influence of a change in FD of a specific nation on EG of the same nation. The short-term spillover and direct effects can be computed by equalizing τ and η to zero.

$$\left(\frac{\partial E(Y_t)}{\partial X_{1k}} \cdots \frac{\partial E(Y_t)}{\partial X_{Nk}}\right) = \begin{bmatrix} \frac{\partial E(Y_{1t})}{\partial X_{1k}} & \cdots & \frac{\partial E(Y_{1t})}{\partial X_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Y_{Nt})}{\partial X_{1k}} & \cdots & \frac{\partial E(Y_{Nt})}{\partial X_{Nk}} \end{bmatrix} = \left((1-\tau)I_N - (\delta + \eta)W\right)^{-1} \begin{bmatrix} \beta_k & \theta W_{12} & \cdots & \theta W_{1N} \\ \theta_k W_{21} & \beta_k & \dots & \theta W_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_k W_{N1} & \theta_k W_{N2} & \dots & \beta_k \end{bmatrix} \quad (2)$$

Yu, Jong, and Lee (2008) suggested a bias-corrected maximum likelihood (ML) estimator for the dynamic SAR and SDM models that include the cross-sectional averages of the explanatory and dependent variables at time t and/or $t-1$ as common factors, or alternatively time period fixed effects can represent the common factors in these models. Their estimator is recently used by Ciccarelli and Elhorst (2018). We adopted the bias-corrected ML estimator to estimate our models that comprise time-period fixed effects and cross-sectional averages of both dependent and independent variables at both time t and $t-1$ as common factors following Ciccarelli and Elhorst (2018). Halleck-Vega and Elhorst (2016) and Ciccarelli and Elhorst (2018) suggested the inclusion of the common factors at time t and $t-1$ together in order to deal with the situation where weak and strong cross-sectional dependences exist at the same time[7]. Weak cross-sectional dependence is identical to spatial dependence which indicates spatial causality among the units, however strong cross-sectional dependence implies correlation. For this reason, ignoring strong cross-sectional dependence leads to biased parameter estimates and unreliable (i.e. spurious) spatial relationships.

Pesaran (2015) suggested a testing procedure where he tests the null of weak cross-sectional dependence against the alternative of strong cross-sectional dependence. His testing routine complements the test developed by Frees (1995) two decades ago, where he tested the null of zero dependence against the alternative of positive dependence among the residuals and units. To infer that the model is specified properly, meaning that the right common factors are controlled for to sort out strong cross-sectional dependence, the null hypotheses of both Pesaran (2015) and Frees (1995) tests should not be rejected. Following Elhorst, Madre, and Pirotte (2020), we applied both tests to obtain robust results.

Parent and LeSage (2011) and (2012) proved that the condition $\eta = -\delta \times \tau$ should be satisfied in order for the spatial model to exhibit empirical regularity. In this study, by following Elhorst (2010) and Elhorst, Madre, and Pirotte (2020) we calculated the probability that $\eta = -\delta \times \tau$ holds to evaluate the empirical regularity of the models. Another issue which closely concerns the soundness of a spatial model is stationarity (or stability). Elhorst (2014) demonstrated that the condition $\tau + \delta + \eta - 1 < 0$ should be fulfilled, together with the rejection of the hypothesis $\tau + \delta + \eta - 1 = 0$, in order to decide that the model in question is stable. In this paper, only the best models which meet the regularity and stationarity conditions are reported.

3. EMPIRICAL FINDINGS AND THEIR INTERPRETATION

To understand whether the panel series FD and EG are stationary we implemented the panel unit root testing methods suggested by Chang (2004) and Uçar and Omay (2009). The estimation results from these procedures are presented in Table 2. According to Table 2, both tests confirm that both panel series are stationary.

Table 2. Panel unit root test results: 1996–2018

Testing procedure	(Uçar and Omay, 2009)	(Chang, 2004)
FD	-1.992** [0.015]	-1.757* [0.054]
EG	-3.261*** [0.001]	-3.039*** [0.004]

Note: Computations depend on 10000 bootstrap replications. Series are de-meaned. Probability values are in brackets. Symbols *, **, and *** imply statistical significance at 10%, 5%, and 1%, respectively.

One should establish the stability and empirical regularity of the spatial models before making any inference concerning the parameter estimates. In addition to this, cross-sectional dependence should also be controlled for by employing the right common factor(s). In the models depicted in Table 3, all of these requirements (or conditions) are fulfilled, meaning that the parameter estimates from these models are reliable in statistical and econometric terms. Furthermore, log-likelihood statistic value does not show a major alteration when we change the specification from SAR to SDM or when the common factor takes different forms.

[7] We followed the same estimation strategy where we also controlled for FD and EG at time t and $t-1$ simultaneously along with all other alternatives to assess and compare the performances of different common factors in resolving the problem of strong cross-sectional dependence. To save space, estimation results for the entire models are not reported in the main text; however they are available upon request. Only the models that provide the best fit are selected and reported in the main text.

One of the most striking finding from the estimations illustrated in Table 3 is that the selected models provide robust parameter estimates. More specifically, the estimates for τ in all selected models point to almost identical significant values (around 0.22). This outcome verifies that the dynamic modelling framework is right. Besides, parameter estimates for β from the models SAR (1) and SDM (1), which employ time period fixed effects as common factors, proved that these models are specified correctly, since these significant and negative estimates for β are almost equal to each other in magnitude (approximately -0.08). This is also the case for models SAR (2) and SDM (2), which also control for the same variable, i.e. EG_{t-1}, as the common factor. The significant estimates for β from these models are around -0.03. In the light of these parameter estimates for β, we conclude that FD affects EG negatively in the sampled emerging economies.

The significant estimates for δ and η, which have opposite signs, proved to be robust as well. To put it more clearly, the strongly significant and positive estimates for δ are very close to one another in magnitude (around 0.75) in all models reported in Table 3. As for η, the significant and negative estimates from all models turned out to be very close to one another in magnitude (around -0.25), signifying robustness. This outcome for δ and η denote that spatial dependence exists in the models selected and reported in Table 3. The estimate for θ is significant in model SDM (1), meaning that when FD of a specific emerging country is associated to the geographical distance, it brings about a negative effect on its own EG when time period fixed effects are controlled for.

When it comes to the spillover effect estimates of FD, illustrated in Table 4, the findings suggest that the short-run estimates are proved to be significant and negative in models SAR (1), SAR (2), and SDM (1). Depending on these estimates, a 1% rise in a specific emerging country's FD leads to a 0.00%, 0.09%, and 0.17% minor falls in the EG rates of all other neighboring emerging market economies. On the other hand, as for the long-run spillovers, SAR (1) is the only model that provides a significant and positive estimate. Depending on these results one can infer that negative spillovers associated with FD magnify the deteriorations in the economic performances of the neighbors in the short run.

Direct effect estimates of FD from all models both in the short and long run are negative and mostly significant. This finding supports the negative estimates for β. The short-run direct effect estimates from SAR (1) and SDM (1) models are very close in magnitude (around -0.08). The direct effect estimates from SAR (2) and SDM (2) models are also very close to each other in the short run (around -0.04). More specifically, one can conclude that a 1% increase in FD causes 0.08% and 0.04% average declines in EG, depending on the estimates from SAR (1) and SDM (1), and SAR (2) and SDM (2) models, respectively.

Table 3: Dynamic spatial panel models with common factors (inverse distance weight matrix)

Dependent variable: EG	**Dynamic spatial panel models**			
Independent variables	SAR (1)	SAR (2)	SDM (1)	SDM (2)
$EG_{it-1}(\tau)$	0.2242 (5.0626)	0.2330 (5.2694)	0.2204 (4.9809)	0.2302 (5.1865)
$\sum_{j=1}^{N} W_{ij} * EG_{jt-1}\ (\eta)$	-0.2603 (-1.9393)	-0.2277 (-1.8921)	-0.2931 (-2.1732)	-0.2232 (-1.8518)
$FD\ (\beta_1)$	-0.0774 (-2.7688)	-0.0290 (-1.7280)	-0.0877 (-3.0438)	-0.0417 (-1.6443)
$W * FD\ (\theta_1)$			-0.1694 (-1.4223)	0.0205 (0.6421)
$\sum_{j=1}^{N} W_{ij} * EG_{jt}\ (\delta)$	0.7716 (7.0793)	0.7553 (21.1898)	0.7295 (6.5058)	0.7500 (20.5803)
σ^2	0.0005	0.0005	0.0005	0.0005
# of observations	460	460	460	460
R^2	0.1377	0.5445	0.1422	0.5440
Common factor(s)	Time period fixed effects	EG_{t-1}	Time period fixed effects	EG_{t-1}
Log-Likelihood	1150.4161	1200.9985	1151.5028	1201.2519
CD test (Pesaran, 2015)	5.675	-0.407	5.592	-0.335
CD test (Frees, 1995)	29.756 [0.097]	16.006 [0.769]	27.781 [0.146]	16.110 [0.763]
$\tau + \delta + \eta - 1$	-0.2645 [0.0939]	-0.2394 [0.0467]	-0.3432 [0.0381]	-0.2431 [0.0440]
Probability $\eta = -\tau * \delta$	0.4973	0.6551	0.3123	0.6627
Note: t-values are in parentheses. Probability values are in brackets.				

Table 4. Short- and long-term effects from the spatial models in Table 3

Model	Independent variable	Short-term effects			Long-term effects		
		Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
SAR (1)	FD	-0.0756 (-2.7203)	-0.0000 (-2.5735)	-0.0757 (-2.7203)	-0.0987 (-2.7053)	0.0243 (1.5274)	-0.0744 (-2.5587)
SAR (2)	FD	-0.0334 (-1.6962)	-0.0856 (-1.6259)	-0.1190 (-1.6617)	-0.0324 (-0.1471)	0.1019 (0.0244)	0.0695 (0.0158)
SDM (1)	FD	-0.0877 (-2.9655)	-0.1702 (-1.4298)	-0.2579 (-1.9969)	-0.1076 (-2.8273)	-0.1351 (-1.1684)	-0.2428 (-1.9933)
SDM (2)	FD	-0.0434 (-1.7657)	-0.0430 (-0.5149)	-0.0864 (-1.0066)	-0.0563 (-1.2670)	-0.0513 (-0.0864)	-0.1077 (-0.1724)
Note: t-values are in parentheses.							

4. CONCLUSION

The nexus between financial development (FD) and economic growth (EG) has been attracting the attention of policy makers, finance and macroeconomics scholars and even the nonprofessionals ever since it was initially discussed in a pioneering study by J. A. Schumpeter in 1911. The topic is important in the sense that it hypothesizes a bridge between the quality and/or efficiency of the financial institutions and/or markets and the real sectors of a national economy. The vast empirical literature which investigates the connection between financial market development and economic activity by employing various empirical procedures shows mixed findings even for similar countries or country groups.

We think that the ambiguity in the related literature may arise from the lack of a dynamic spatial perspective. For this reason, we employed dynamic spatial panel models to examine the relationship between FD and EG for a selected sample of 20 emerging market economies by using annual data covering the period 1996-2018. We also controlled for different forms of common factors to sort out the problem of strong dependence among the cross-sectional units. We establish unbiased parameter estimates and thus genuine spatial dependence by so doing.

The estimation results point to a negative relationship between FD and EG, meaning that financial sector improvement leads to a fall in economic activity in the sampled emerging countries. We also found supporting evidence from the estimations of the direct effects. As for the spillovers, estimations proved that there also exists a deteriorating impact from a specific nation to all its neighbors' EG rates when that nation's financial system develops. These findings we think are quite intriguing on the grounds that they revive the old debate that financial development may be detrimental to EG rates in the developing economies, instead of being an engine for growth. This negative relationship may be the result of the broken link between the financial and real sectors of the emerging market economies. Policy makers in the sampled countries should keep the financial sectors under control by regulations so as to stabilize their EG rates. Besides, they should design eoconomic policy measures to prevent their economic performances from falling due to the negative spillovers transmitted from the neighboring countries that show progress in their financial sectors

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APPENDIX

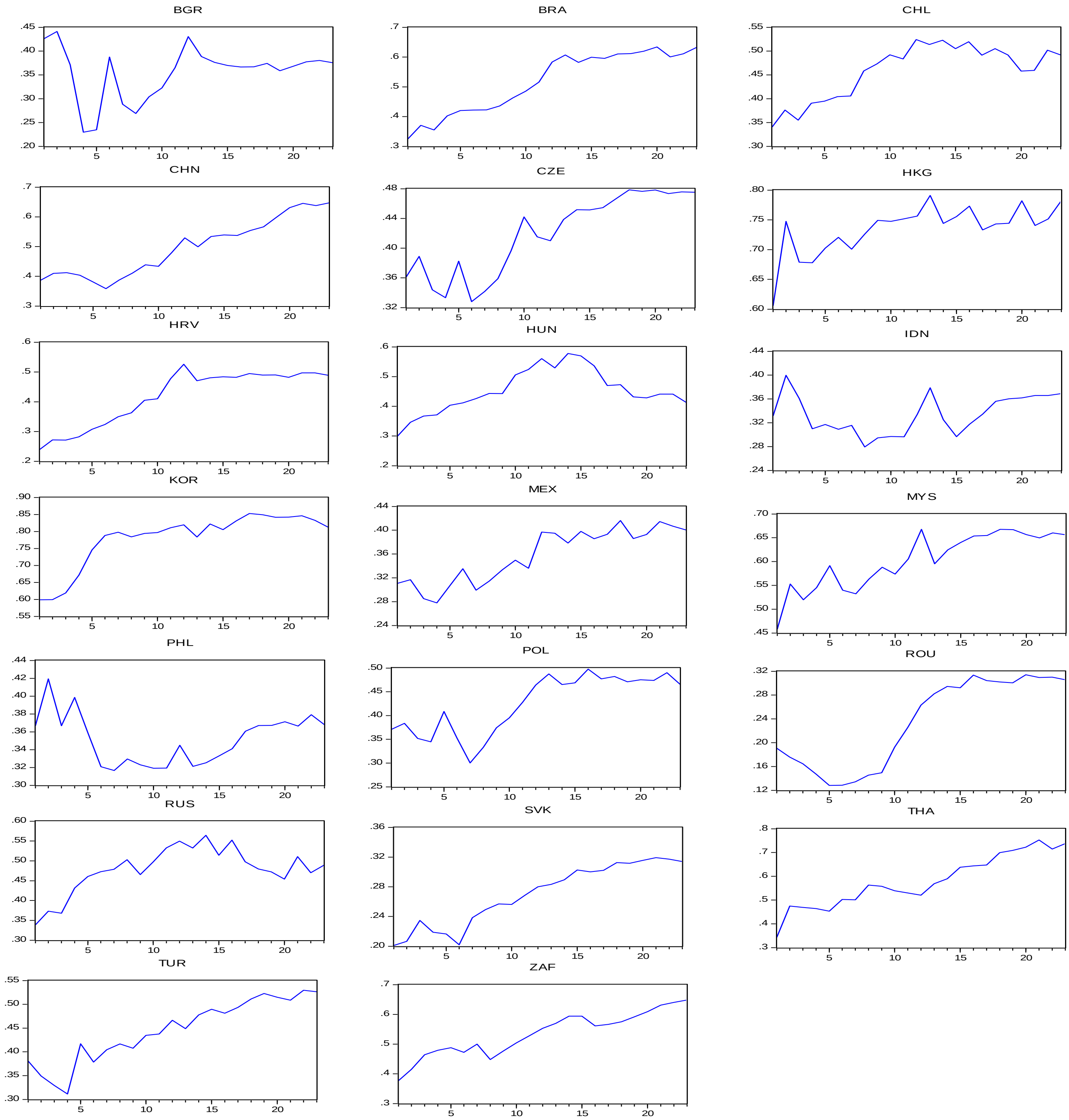

Figure A1: FD series for individual countries: 1996-2018

Table A1. Descriptive statistics of individual countries for FD

	BGR	BRA	CHL	CHN	CZE	HKG	HRV	HUN	IDN	KOR
Mean	0.355379	0.517601	0.459138	0.496648	0.418350	0.734941	0.416661	0.452649	0.333793	0.780222
Median	0.370002	0.582094	0.483694	0.499568	0.438625	0.744216	0.477334	0.441156	0.331553	0.805428
Maximum	0.441305	0.633827	0.524203	0.647269	0.478430	0.790875	0.525816	0.577758	0.399765	0.852783
Minimum	0.229678	0.325192	0.340494	0.358719	0.327869	0.605537	0.239403	0.299384	0.279456	0.598593
Std. Dev.	0.056177	0.103575	0.057439	0.095906	0.053638	0.040968	0.093037	0.073510	0.032421	0.079464
Skewness	-0.866122	-0.421312	-0.717868	0.203165	-0.385440	-1.440354	-0.645678	0.011909	0.192954	-1.434288
Kurtosis	3.144549	1.627617	2.155351	1.673261	1.655112	5.499337	1.832372	2.394521	1.990270	3.698695
Observations	23	23	23	23	23	23	23	23	23	23

Table A1. continued

	MEX	MYS	PHL	POL	ROU	RUS	SVK	THA	TUR	ZAF
Mean	0.357803	0.602749	0.351502	0.424424	0.233648	0.478649	0.269419	0.580024	0.445154	0.534206
Median	0.378451	0.605607	0.358992	0.464014	0.263008	0.479678	0.280064	0.562756	0.448933	0.552838
Maximum	0.416150	0.667827	0.419403	0.497580	0.314174	0.564326	0.319206	0.753043	0.529738	0.648437
Minimum	0.277793	0.458071	0.316623	0.300165	0.128244	0.338806	0.201152	0.343131	0.311477	0.376772
Std. Dev.	0.045194	0.058931	0.027963	0.061207	0.073924	0.057874	0.041414	0.109914	0.065361	0.074051
Skewness	-0.315412	-0.648999	0.520496	-0.485158	-0.240230	-0.858660	-0.359115	-0.063152	-0.461511	-0.289165
Kurtosis	1.612001	2.553489	2.652590	1.795355	1.312652	3.345290	1.694047	2.191363	2.154554	2.208329
Observations	23	23	23	23	23	23	23	23	23	23

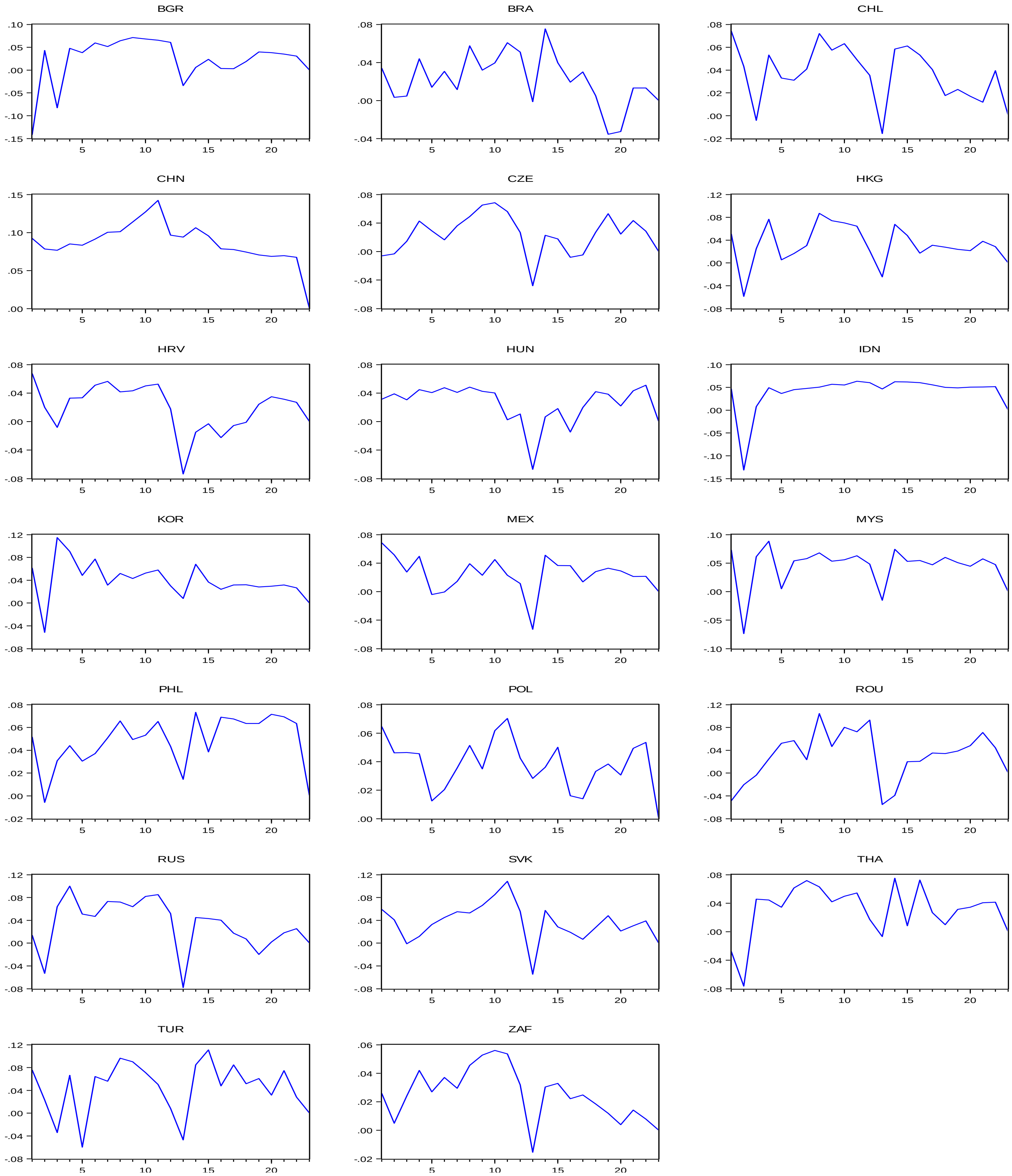

Figure A2: EG series for individual countries: 1996-2018

Table A2: Descriptive statistics of individual countries for EG

	BGR	BRA	CHL	CHN	CZE	HKG	HRV	HUN	IDN	KOR
Mean	0.022199	0.022127	0.037205	0.086581	0.023997	0.032303	0.019800	0.025163	0.040259	0.040231
Median	0.038115	0.019212	0.040450	0.084915	0.026823	0.028616	0.026947	0.038456	0.050309	0.032025
Maximum	0.071535	0.075282	0.074279	0.142314	0.068535	0.087001	0.067528	0.050940	0.063450	0.114669
Minimum	-0.141928	-0.035458	-0.015642	0.000627	-0.048026	-0.058827	-0.073594	-0.066996	-0.131267	-0.051294
Std. Dev.	0.050770	0.027406	0.024280	0.026708	0.027439	0.033859	0.032250	0.026962	0.040413	0.032688
Skewness	-1.859844	-0.223519	-0.490108	-0.940043	-0.549078	-0.643723	-0.988538	-1.903234	-3.573982	-0.326874
Kurtosis	6.299552	2.852505	2.463875	6.370421	3.323018	3.684188	4.083203	6.933813	15.50952	4.744289
Observations	23	23	23	23	23	23	23	23	23	23

Table A2: continued

	MEX	MYS	PHL	POL	ROU	RUS	SVK	THA	TUR	ZAF
Mean	0.024630	0.044740	0.048305	0.038360	0.030433	0.032706	0.036305	0.031035	0.045131	0.025294
Median	0.027536	0.053910	0.051854	0.038391	0.035146	0.043000	0.038967	0.040663	0.056083	0.026000
Maximum	0.068469	0.088589	0.073345	0.070352	0.104281	0.100001	0.108320	0.075134	0.111135	0.056038
Minimum	-0.052857	-0.073594	-0.005767	0.000535	-0.055174	-0.078000	-0.054555	-0.076340	-0.059623	-0.015381
Std. Dev.	0.024734	0.035015	0.022319	0.017639	0.042974	0.043630	0.032886	0.035315	0.045695	0.018208
Skewness	-1.136938	-2.006947	-1.026562	-0.261222	-0.408901	-0.810846	-0.447210	-1.301923	-0.900808	-0.174415
Kurtosis	5.445096	6.989148	3.223227	2.536140	2.545025	3.350823	4.354579	4.892603	3.000680	2.607913
Observations	23	23	23	23	23	23	23	23	23	23