THE INFLUENCE OF FDI ON DOMESTIC INNOVATION: AN INVESTIGATION USING STRUCTURAL BREAKS

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Abstract

This paper investigates the influence of foreign direct investment on innovation by employing the panel cointegration method incorporating multiple structural breaks and a dynamic common correlated estimation for 34 countries over the period 1991–2016. Our findings indicate that the series of innovation and foreign direct investment are stationary after considering the potential structural breaks and that the external shock is mainly from country-specific shocks. Our results also suggest that a long-run co-integrated relationship exists with one break between foreign direct investment and innovation. Furthermore, the estimation based on the dynamic common correlated estimation shows that foreign direct investment has a long-run significant positive influence on technological innovation. Our findings shed light on the importance of accounting for structural breaks when discussing the relationship between foreign direct investment and technological innovation.

Keywords: Innovation, patent, trademark, FDI, structural breaks, cointegration

JEL Classification: C33, O34, F23

1. Introduction

With the expectation that foreign firms exhibit technology spillover and labour pooling, most countries implement generous preferential policies and relaxed business environments to attract foreign direct investment (FDI) (Javorcik and Spatareanu, 2011). However, the empirical literature for the spillover effect of FDI has produced ambiguous results. For example, Cheung and Lin (2004) find that FDI can improve innovation activities through the channels of reverse engineering, skilled labour turnover, demonstration effects, and supplier-customer relationships (Haskel *et al.*, 2007). By contrast, Aitken and Harrison (1999) note that FDI has a negative impact on the productivity of wholly domestically

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owned firms (Lu *et al.*, 2017). Innovation also entails more FDI from multinational firms, which explore capabilities available in the host country to pursue sustainable competitiveness (Chen and Yeh, 2012). These findings concentrate on one direction only, from FDI to innovation, but an issue hence arises: Do FDI and innovation move together? More particularly, since the structural break is a common phenomenon in economic series (Chang and Lee, 2015), do we need to take multiple breaks into consideration?

By employing the panel cointegration test with structural breaks, the goal of this paper is to examine the long-run relationship between innovation and FDI based on panel data over the period 1991–2016 in 34 countries. More specifically, we not only account for multiple breaks in the panel unit root test, but also utilize the panel cointegration test with structural breaks proposed by Westerlund and Egerton (2008) and Banerjee and Carrion-i-Silvestre (2015). Next, we use the growth rate of patents and trademarks (*Patent* and *Trademark*) and the growth rate of FDI (*FDI*) as measurements for innovation and FDI, respectively. In addition, to investigate the influence of FDI on innovation, we employ the panel dynamic common correlated estimation (DCCE) model. We believe that our research provides additional evidence of the relationship between innovation and FDI, as well as evidence from incorporating multiple breaks in the panel cointegration test.

The effect of FDI on technological innovation in recent years has drawn widespread scholarly attention. Many studies in the literature claim that FDI is associated with increased innovation performance (Liang *et al.*, 2017). Vahter (2011) finds that the presence of FDI contributes to subsequent process and product innovation for these incumbents, indicating the existence of a technology transfer channel (Li *et al.*, 2017). However, many studies hold that the technology spillover of FDI is conditional to various factors (Joen *et al.*, 2013; Girma *et al.*, 2015). As Madsen *et al.* (2010) state, technology spillover cannot appear automatically as mastering technology needs enough time, resources, investment in knowledge, and training for technicians and engineers. Malik (2015) shows that technology spillovers from FDI are constrained by absorptive capacity and ownership structure. Some empirical results show a negative effect of FDI on innovation. Stiebale and Reize (2011) find that foreign acquisitions exert a negative influence on average R&D expenditures and innovation activities.

The existing literature also notes that knowledge seeking is a critical factor affecting the location choice of FDI (Kim and Aguilera, 2016). International enterprises do not look solely for new market and natural resources, but also seek access to advanced technology and knowledge assets (Dunning, 2000; Ramasamy *et al.*, 2012). Santangelo and Meyer (2011) present that firms tend to acquire innovative capability and technological know-how overseas. Cui *et al.* (2014) note that advanced technology is a crucial target that firms seek

to obtain through FDI. Nielsen *et al.* (2017) also point out that a firm's technological knowledge is generally a positive driver for its internationalization.

More importantly, the literature demonstrates that it is necessary to consider the structural break in the cointegration test. As Westerlund (2006) offers, structural breaks are usually observed in macroeconomic series, such as real output and trade. Thus, ignoring them in an estimated model will lead to biased results. From the literature, we find that the FDI series exhibit structural breaks in the unit root test (Sbia *et al.*, 2014; Solarina and Shahbaz, 2015) and the cointegration test (Seker *et al.*, 2015). Hence, to investigate the long-run influence of FDI on innovation, we do not simply consider structural breaks in the unit root test and cointegration test, but also incorporate the estimated break point in the regression model, providing more detailed and powerful results.

Our results indicate that *FDI*, *Patent*, and *Trademark* follow a stationary trend under the panel Lagrange Multiplier (LM) unit root test with structural breaks. The PANICCA test further shows that the non-stationarity of structural shifts mainly comes from country-specific factors. The results of the panel cointegration test reveal a long-run cointegration relationship between *FDI* and *Patent* as well as between *FDI* and *Trademark* when structural breaks are considered. The DCCE estimation hence indicates that FDI has a positive influence on innovation.

The rest of this paper runs as follows. Section 2 presents a brief introduction about the panel unit root test with structural breaks, the panel cointegration test with multiple structural breaks, and the dynamic common correlated estimator. Section 3 provides the data source and variables and discusses the empirical results. Section 4 concludes.

2. Methodology

2.1 Panel unit root tests with structural breaks

In this section we follow the panel LM unit root test with level structural breaks developed by Im *et al.* (2005) to check for panel stationarity of the variables. The panel LM unit root test of Im *et al.* (2005) can account for potential unknown structural breaks among series and test the unit root in every cross-section. Hence, the data-generating process is:

$$y_{it} = \gamma_{1i} + \gamma_{2i}t + \delta_i TB_{it} + x_{it}, \quad (1)$$

where y_{it} denotes *FDI* or both innovation variables in the country i at the time t ; $t = 1, \dots, T$ represents time periods; $i = 1, \dots, N$ represents the number of cross-sections; $x_{it} = \phi_t x_{it-1} + \varepsilon_{it}$; $TB_{it} = 1$ for $t > BP_i$ and 0 otherwise; BP_i represents the break point in the country i ; and ε_{it} is the zero-mean error term.

The idea of Im *et al.* (2005) to construct the panel LM unit root test statistics is averaging the univariate LM test statistics for each country. Thus, before computing the panel LM test statistics, we have to get the univariate LM unit root statistics in each country. Amsler and Lee (1995) show that the LM statistics for the country i are obtained as a t -statistic from testing $\varphi = 0$ in the regression:

$$\Delta y_{it} = \gamma_{2i} + \delta_i TB_{it} + \varphi S_{i,t-1} + \mu_{it}, \quad (2)$$

where $S_{i,t-1}$ is the de-trended lagged dependent variable $y_{i,t-1}$; and μ_{it} is the stochastic term. Let LM_i represent the univariate LM unit root statistics for the country i ; hence, the panel unit root statistics are given by $LM_{NT} = (1/N) \sum_{i=1}^N LM_i$. The standardized panel LM unit root test statistics are:

$$\Gamma_{LM} = \frac{\sqrt{N}(LM_i - E(\tau_{LM}))}{\sqrt{V(\tau_{LM})}}. \quad (3)$$

Here, $E(\tau_{LM})$ and $V(\tau_{LM})$ correspondingly denote the expected value and variance of τ_{LM} for the case where there are no structural shifts in the series. Im *et al.* (2005) show that the presence of structural shifts does not affect the asymptotic distribution of these panel LM statistics as they follow the standard normal distribution.

The PANICCA test (combing principal components-based panel analysis of non-stationarity in idiosyncratic and common components, “PANIC” and cross-section average, “CA”) developed by Reese and Westerlund (2016) is also utilized to analyse the structural break shifts whether from the common factors or from idiosyncratic components. The PANICCA test of Reese and Westerlund (2016) has the advantage of distinguishing the underlying sources of non-stationarity. The data-generating process is as follows:

$$y_{it} = \phi'_i D_{t,p} + \eta'_i G_t + e_{it}, \quad (4)$$

where $D_{t,p}$ refers to a polynomial trend function given as $D_{t,p} = (1, \dots, t^p)'$ with $(p+1) * 1$ trend; G_t implies an $r * 1$ vector of common factors; η_i is the corresponding factor loading; e_{it} is the unit-specific idiosyncratic error term; and $D_{t,p}$ has two options: $p = 0$ for the intercept only and $p = 1$ for both intercept and trend. Whether the estimated $\tilde{G}_t$ and $\tilde{e}_{it}$ are stationary is tested through $\tilde{G}_t = \rho \tilde{G}_{t-1} + u_t$ and $\tilde{e}_{it} = \gamma \tilde{e}_{i,t-1} + v_{it}$. For the stationarity of $\tilde{e}_{it}$, Reese and Westerlund (2016) propose three statistics represented by Pap, Pbp, and PMSBp for the two cases of $p = 0$ and $p = 1$. For the stationarity of $\tilde{G}_t$, the augmented Dickey–Fuller (ADF) statistics are carried out following the suggestion in Bai and Ng (2004).

2.2 Panel cointegration tests with structural breaks

Westerlund and Edgerton (2008) develop a simple test with two statistics in order to examine the null hypothesis of no cointegration in panel data. Compared with the conventional panel cointegration test, the main advantage of the Westerlund and Edgerton (2008) cointegration test is that it considers cross-section dependence and unknown heterogeneous shifts in both the constant and the slope of the cointegrated regression. Consider the following model:

$$y_{it} = \theta_i + \omega_i B_{it} + x'_{it} \beta_i + (B_{it} x_{it})' \gamma_i + z_{it} \quad (5)$$

$$x_{it} = x_{it-1} + \mu_{it} \quad (6)$$

The k -dimensional vector x_{it} represents the regressors and is defined as a random walk. Here, D_{it} denotes the break point such that $D_{it} = 1$ for $t > T_i$ and 0 otherwise; θ_i and β_i refer to the intercept and slope before the shift, while ω_i and γ_i refer to the change in the intercept and slope after the shift; and z_{it} is the zero-mean error term, which is independent across units. We now present the disturbance term μ_{it} , which takes cross-sectional dependence into account by including the unobserved common factors:

$$\mu_{it} = \lambda_i G_t + v_{it} \quad (7)$$

$$F_{jt} = \rho_j F_{jt-1} + u_{jt} \quad (8)$$

$$\phi_i(L) \Delta v_{it} = \phi_i v_{it-1} + e_{it} \quad (9)$$

We note that $\phi_i(L) = 1 - \sum_{j=1}^{p_i} \phi_{ij} L^j$ indicates a scalar polynomial in the lag operator L ; G_t shows the vector of unobservable common factors; λ_i means the vector of corresponding factor loading; v_{it} is independent of e_{it} and μ_{it} for all i and t ; and e_{it} is an error term with zero mean. The null hypothesis in Westerlund and Edgerton (2008) is that all individuals are cointegrated, while the alternative one is that the first M individuals are cointegrated while the others are not. Thus, the panel cointegration test statistics proposed by Westerlund and Edgerton (2008) are given as:

$$Z_\phi(N) = \sqrt{N} (\overline{LM}_\phi - E(B_\phi)) \quad (10)$$

$$Z_\tau(N) = \sqrt{N} (\overline{LM}_\tau - E(B_\tau)), \quad (11)$$

where $\overline{LM}_\phi = (1/N) \sum_i^N LM_\phi(i)$, $\overline{LM}_\tau = (1/N) \sum_i^N LM_\tau(i)$, $LM_\phi(i) = T \hat{\phi}_i(\hat{\omega}_i / \hat{\sigma}_i)$, $LM_\tau(i) = \hat{\phi}_i / SE(\hat{\phi}_i)$, and $\hat{\phi}_i$ is the estimated ϕ_i in Equation 9 of Westerlund and Edgerton (2008).

Banerjee and Carrion-i-Silvestre (2015) design a procedure to test a cointegrated relationship. The Banerjee and Carrion-i-Silvestre (2015) panel cointegration test allows for structural breaks in both the deterministic components and the cointegrating vector and also takes cross-section dependence among units into account. The data-generating process with structural form is given as:

$$y_{it} = D_{it} + x'_{it} \delta_{it} + u_{it} \quad (12)$$

$$u_{it} = F'_t \pi_i + e_{it} \quad (13)$$

$$(I - L)F_t = C(L)w_t \quad (14)$$

$$(1 - \rho_i L)e_{it} = H_i(L)\varepsilon_{it} \quad (15)$$

$$x_{it} = \kappa_i + x_{it-1} + G'_t \zeta_i + \Xi(L)v_{it} \quad (16)$$

$$G_t = \Gamma(L)\varpi_t, \quad (17)$$

where $t = 1, \dots, T$ represent time period; $i = 1, \dots, N$ represent units; y_{it} and x_{it} are respectively the scalar and the vector of a stochastic process whose elements follow $I(1)$; $C(L)$ $C(L) = \sum_{j=0}^{\infty} C_j L^j$; $H_i(L) = \sum_{j=0}^{\infty} h_{ij} L^j$; $\Xi_i(L) = \sum_{j=0}^{\infty} \Xi_{ij} L^j$; and $\Gamma(L) = \sum_{j=0}^{\infty} \Gamma_j L^j$. Here, the deterministic term D_{it} is formulated by:

$$D_{it} = \mu_i + \beta_i t + \sum_{j=1}^{m_i} \theta_{ij} DU_{ijt} + \sum_{j=1}^{m_i} \gamma_{ij} DT_{ijt}, \quad (18)$$

where $DU_{ijt} = 1$ and $DT_{ijt} = t - T_{ij}$ for $t > T_{ij}$ and 0 otherwise; and T_{ij} implies the time period of the j^{th} breaks, $j = 1, \dots, m_i$ for individual i . The cointegrating vector is a function of time, and hence:

$$\delta_{it} = \delta_{ij} \text{ for } T_{ij-1}^c < T_{ij}^c \quad (19)$$

We note that $T_{i0}^c = 0$, $T_{i,n_i+1}^c = T$, and T_{ij}^c represent the time of the j^{th} break, $j = 1, \dots, n_i$ for the unit i . In this study we use Model 5 in Banerjee and Carrion-i-Silvestre (2015) as it accounts for the presence of multiple structural break effects on both the level and the cointegrating vector of the model and allows unobservable structural breaks. The null hypothesis is that there is no panel cointegration in all units. In the process of constructing the panel statistics, Banerjee and Carrion-i-Silvestre (2015) first take the orthogonal projections with respect to deterministic components and thus estimate the common factors and factor loadings by employing principal components. Next, they recover the idiosyncratic error term through accumulation and test the unit root using ADF-type

regression and the pseudo t -ratio $t_{\hat{\epsilon}_i^*}^\tau$. Hence, the panel cointegration test statistics are constructed based on the sum of the individual ADF cointegration tests:

$$SADF_\tau(\lambda) = \sum_{i=1}^N t_{\hat{\epsilon}_i^*}^\tau \quad (20)$$

The limiting distribution of these statistics is given by:

$$Z_\tau(\lambda) = \frac{N^{-1/2} SADF_\tau(\lambda) - \Theta_\tau^e(\lambda) \sqrt{N}}{\sqrt{\Psi_\tau^e(\lambda)}} \Rightarrow N(0,1) \quad (21)$$

where the detailed formula of $\Theta_\tau^e(\lambda)$ and $\Psi_\tau^e(\lambda)$ can be found in Theorem 2 of Banerjee and Carrion-i-Silvestre (2015). Note that we use Bai and Ng's (2004) BIC to obtain the optimum number of factors.

2.3 Dynamic common correlated estimator

To examine the influence of FDI on innovation, we employ the dynamic common correlated effects estimator proposed by Chudik and Pesaran (2015). The DCCE model has the advantages of controlling the dynamics of the dependent variable, dealing with potential endogeneity problems, and accounting for the cross-sectional dependence and heterogeneous slope coefficients through cross-sectional averages.¹ The DCCE model that we use in this study is given as:

$$Innovation_{it} = c_i + \alpha Innovation_{it-1} + \beta FDI_{it} + \gamma' X_{it} + \xi_i' G_t + \mu_{it}, \quad (22)$$

where $Innovation_{it}$ represents the variable for innovation; FDI denotes foreign direct investment; X_{it} stands for some control variables, including economic development ($Lngdpp$), openness ($Trade$), population ($Lnpop$), urbanization ($Urban$), and estimated break points (BP); c_i implies the country-specific effect; G_t refers to the unobservable common factors, reflecting the global shocks; and μ_{it} is the idiosyncratic errors that are serially correlated and weakly independent across countries.

To account for the common factor effect, we add the cross-sectional averages of the innovation variable and its lagged terms as well as the FDI variable to the dynamic panel model. Hence, the equation becomes:

$$Innovation_{it} = c_i + \alpha Innovation_{it-1} + \beta FDI_{it} + \gamma' X_{it} + \sum_{k=0}^{P_T} \phi_k' \overline{z_{t-k}} + \mu_{it}, \quad (23)$$

where $\overline{z_{t-k}} = (\overline{Innovation_{it}}, \overline{Innovation_{it-1}}, \overline{FDI_{it}}, \overline{X_{it}})$ is the cross-sectional average of the dependent variable and the independent variable; and P_T shows the lag number

¹ The DCCE model provides more reliable and powerful results versus the pooled OLS model, the panel fixed-effects model, the panel random-effects model, and the general dynamic panel model.

of cross-sectional average. Following Chudik and Pesaran (2015), the mean group estimates are given by:

$$\widehat{\pi}_{MG} = \frac{1}{N} \sum_{i=1}^N \widehat{\pi}_i, \quad (24)$$

where $\widehat{\pi}_i = (\widehat{\alpha}, \widehat{\beta}, \widehat{\gamma}_i)'$ are obtained from the least square estimation for regression (23). The asymptotic distribution is hence developed as:

$$\sqrt{N}(\widehat{\pi}_{MG} - E(\pi_i)) \Rightarrow N(0, \Sigma_{MG}) \quad (25)$$

Note that $\Sigma_{MG} = \frac{1}{N-1} \sum_{i=1}^N (\widehat{\pi}_i - \widehat{\pi}_{MG})(\widehat{\pi}_i - \widehat{\pi}_{MG})'$.

3. Empirical Description

3.1 The data and variables

This paper uses panel data for the period 1991–2016 in 34 countries. We gather *Patent* and *Trademark* from the World Intellectual Property Organization (WIPO). Additionally, the variable *FDI* is taken from the World Development Indicators (WDI) of the World Bank. Specifically, we employ the growth rate to the proxies *Patent*, *Trademark*, and *FDI*.² It is worth noting that *FDI* is adjusted by purchasing power parity (PPP), which is the reason why the sample beginning year is 1991 as the converting factor to PPP appears in 1990, and the sample includes 34 countries as the panel unit root test needs balanced panel data.

In an effort to get evidence of the long-run influence of FDI on innovation, we plot the time series of the mean growth rate of *Patent* – *FDI* as well as *Trademark* – *FDI* in Figure 1. Figure 1a and Figure 1b correspond to *Patent*–*FDI* and *Trademark* – *FDI*, respectively. As can be seen in Figure 1a, there is an intuitive co-movement between the patent growth rate and the FDI growth rate. In particular, *Patent* and *FDI* show similar trends in the periods 1992–2002 and 2008–2016, indicating that there may exist a long-run co-movement relationship between the two. We also find that there is a break point in the co-movement of *Patent* and *FDI*. For instance, the patent growth rate shows a decreasing trend, while the FDI growth rate exhibits the opposite trend. Similarly, Figure 1b shows the same trends for *Trademark* and *FDI*. Therefore, these trends in Figure 1 emphasize the importance of considering structural breaks in investigating the influence of FDI on innovation.

2 We are grateful to two referees for providing this advice.

Figure 1: Plots of innovation and FDI (1991–2016)

(a) Patent–FDI

(b) Trademark–FDI

Source: Authors' calculations.

3.2 Empirical results

3.2.1 Results of panel unit root test with structural breaks

Using the method proposed by Im *et al.* (2005), we estimate the individual-specific break point for each country and compute the panel statistics to verify the stationarity of the whole series. Table 1 presents the results of the panel LM unit test with structural breaks. As can be seen, the panel test statistics in all the models reject the null hypothesis of unit root with structural shifts, showing that the series of *Patent*, *Trademark*, and *FDI* are stationary when considering structural breaks. The individual LM unit root test statistics are significant in all the countries, suggesting that these variables in each country do not have unit roots under potential structural breaks. We also find that 22 out of 33 countries indicate a break point in 2001 for the variable *FDI*, showing a large fluctuation of FDI inflow in 2001. Overall, the results of our panel LM unit root test with structural breaks support the notion that it is necessary to account for structural breaks for examining the stationarity of innovation as well as FDI.

Even though the panel LM unit root test helps us understand the stationarity of innovation and FDI, it does not offer detailed information about the source of non-stationarity. The PANICCA test proposed by Reese and Westerlund (2016) is thus used to distinguish the source of non-stationarity from common shock and unit-specific shock. Table 2 reports the results of the PANICCA test where $P = 0$ denotes the model solely with intercept and $P = 1$ denotes the model with both intercept and trend. The results suggest that non-stationary shocks appear in *Patent*, *Trademark*, and *FDI*, which are mainly due to country-specific error/shocks since all the statistics for idiosyncratic component are not significant. Nevertheless, all the ADF statistics are significant at the conventional level, reflecting that the global trend only induces a temporary fluctuation in *Patent*, *Trademark*, and *FDI* and that these trends will disappear in the long run.

Table 1: Panel LM unit root test with one break

	Patent			Trademark			FDI		
Country	LM	P	BP	LM	P	BP	LM	P	BP
Argentina	-3.555*	7	2012	-4.918 *	8	2004	-4.242 *	3	2001
Austria	-3.533 *	8	2002	-4.533 *	1	2002	-6.169 *	0	2001
Bangladesh	-4.219 *	8	2009	-4.142 *	8	2005	-4.026 *	5	2012
Brazil	-4.264 *	8	2006	-3.757 *	5	2013	-4.107 *	8	2001
Bulgaria	-3.978 *	6	2009	-6.094 *	8	2006	-5.468 *	8	2001
Canada	-3.900 *	6	2007	-4.015 *	8	2002	-5.348 *	2	2001
Chile	-3.216 *	7	2008	-4.690 *	6	2013	-5.303 *	8	2007
Denmark	-3.558 *	0	2012	-4.994 *	8	2004	-5.125 *	3	2001
Finland	-5.201 *	5	2002	-7.032 *	8	2011	-4.474 *	0	2003
France	-4.028 *	1	2003	-3.843 *	1	2013	-5.460 *	8	2002
Germany	-3.480 *	1	2005	-3.632 *	7	2001	-6.286 *	7	2001
Iceland	-3.988 *	2	2008	-4.566 *	1	2004	-5.448 *	7	2001
India	-3.873 *	8	2008	-5.768 *	7	2010	-5.015 *	1	2001
Ireland	-7.156 *	7	2007	-5.196 *	5	2010	-5.612 *	6	2001
Israel	-4.108 *	7	2003	-5.385 *	8	2003	-9.393 *	8	2001
Italy	-3.784 *	2	2004	-4.025 *	1	2006	-4.582 *	8	2001
Japan	-4.638 *	8	2004	-4.033 *	1	2005	-6.053 *	7	2011
Korea, South	-3.882 *	1	2011	-5.091 *	1	2001	-4.551 *	5	2002
Malaysia	-3.627 *	0	2009	-2.803 *	0	2009	-6.809 *	6	2010
Mexico	-6.092 *	6	2013	-6.412 *	6	2006	-4.893 *	2	2013
New Zealand	-7.001 *	5	2012	-5.659 *	8	2007	-4.347 *	1	2001
Norway	-4.037 *	1	2010	-4.270 *	7	2006	-5.272 *	0	2001
Philippines	-3.362 *	7	2006	-6.984 *	7	2002	-4.126 *	7	2001
Poland	-3.781 *	0	2006	-3.915 *	1	2003	-4.326 *	3	2012
Portugal	-5.956 *	8	2011	-3.716 *	0	2004	-3.863 *	7	2003
Romania	-4.926 *	7	2002	-4.568 *	8	2005	-5.819 *	8	2001
South Africa	-4.137 *	2	2003	-3.682 *	7	2001	-3.984 *	8	2001
Spain	-3.449 *	5	2006	-4.880 *	5	2007	-3.793 *	0	2002
Sweden	-3.431 *	5	2010	-4.262 *	7	2004	-3.772 *	1	2013
Switzerland	-3.812 *	7	2005	-6.261 *	8	2003	-9.057 *	8	2001
Turkey	-3.958 *	5	2009	-6.266 *	7	2010	-3.396 *	0	2001
United Kingdom	-3.393 *	8	2001	-4.373 *	5	2009	-7.789 *	7	2001
United States	-4.254 *	8	2007	-3.412 *	8	2004	-4.331 *	5	2001
Vietnam	-6.661 *	8	2001	-5.998 *	8	2002	-4.560 *	0	2001
Panel test statistics	-43.403 ^a			-35.304 ^a			-11.182 ^a		

Notes: P and BP denote optimal lags and estimated break point, respectively. * corresponds to significance at the 5% level.

Source: Authors' calculations.

Table 2: PANICCA test

	Common Factors		Idiosyncratic Component					
Variable	P = 0	P = 1	P = 0			P = 1		
	ADF	ADF	Pap	Pbp	PMSBp	Pap	Pbp	PMSBp
Patent	−4.886	−4.777	2.471	3.370	1.907	0.705	0.869	1.045
p-value	0.001	0.001	0.993	0.999	0.972	0.759	0.807	0.852
Trademark	−4.953	−4.835	1.133	1.101	0.148	−0.141	−0.139	−0.083
p-value	0.001	0.001	0.871	0.864	0.559	0.444	0.445	0.467
FDI	−5.070	−5.086	−0.174	−0.198	0.470	0.361	0.409	0.492
p-value	0.001	0.001	0.431	0.422	0.681	0.641	0.659	0.689

Source: Authors' calculations.

3.2.2 Results of panel cointegration test with structural breaks

As we have confirmed that *Patent*, *Trademark*, and *FDI* show stationarity with structural break, we next examine whether there exists a long-run cointegrated relationship between innovation and FDI. The results of the panel cointegration test with structural shifts developed by Westerlund and Egerton (2008) are presented in Table 3. The cointegration results in Panel B of Table 3 indicate that the null of no integration could be rejected at the 1% level in the regime-shift model with breaks in both intercept and slope. In fact, the results in the no-shift model also show a co-movement for *Patent*–*FDI* and *Trademark*–*FDI*. However, the statistics in the no-shift model are less powerful as they turn out to be insignificant after accounting for the shift in the intercept in the model. Based on these results, we confirm a cointegration relationship with structural breaks between innovation and FDI. Accordingly, the results further indicate that it is necessary to consider multiple structural breaks in the estimation of the panel long-run cointegration test.

The results of Panel A in Table 3 also exhibit the locations of structural breaks. It is worth noting that the year 2000 shows a structural break in most countries for the *Trademark*–*FDI* model. This reflects a fluctuation in the cointegrated relationship between *Trademark* and *FDI*. A possible explanation is that transnational terrorism, such as the terrorist attacks of 11 September 2001, has led to huge fluctuations in FDI. As Powers and Choi (2012) argue, business-related terrorism can reduce FDI flows by damaging buildings, destroying products, killing workers, and raising insurance expenditures (Enders *et al.*, 2006).

Table 3: Panel cointegration test of Westerlund and Edgerton (2008)

Panel A: Estimated break point					
Country	Patent-FDI	Trademark-FDI	Country	Patent-FDI	Trademark-FDI
Argentina	1993	2003	Korea	1997	2000
Austria	1995	1995	Malaysia	1999	2000
Bangladesh	1996	2006	Mexico	1994	1993
Brazil	1993	2006	New Zealand	1995	1998
Bulgaria	1997	2000	Norway	1995	2000
Canada	1999	2000	Philippines	2007	1997
Chile	2012	1995	Poland	2010	2000
Denmark	2010	2000	Portugal	1998	2000
Finland	2000	2000	Romania	2002	1997
France	1993	2000	South Africa	1996	2000
Germany	2008	1996	Spain	2009	1998
Iceland	1996	1995	Sweden	2002	1993
India	2009	1997	Switzerland	2000	1995
Ireland	1997	2000	Turkey	1996	2004
Israel	1999	2010	United Kingdom	1995	2000
Italy	2009	2004	United States	1993	1994
Japan	1995	1998	Vietnam	2000	2002

Panel B: Cointegration test with shift				
	Patent-FDI		Trademark-FDI	
	Z_{τ}	Z_{ϕ}	Z_{τ}	Z_{ϕ}
No shift	-9.426	-11.987	-7.330	-11.201
p-value	0.000	0.000	0.000	0.000
Level shift	-0.169	0.376	0.548	0.275
p-value	0.433	0.647	0.708	0.608
Regime shift	-2.604	-2.259	-9.861	-14.173
p-value	0.005	0.012	0.000	0.000

Panel C: DOLS estimation		
Dependent variables	Independent variables	Panel
Patent	FDI	0.004 (1.979) *
FDI	Patent	-23.500 (0.432)
Trademark	FDI	0.001 (-2.352) *
FDI	Trademark	-143.400 (-1.944) **

Notes: Z_{τ} and Z_{ϕ} represent two different statistics of panel cointegration with structural break in Westerlund and Edgerton (2008). No shift implies no break. Level shift implies one break in the intercept. Regime shift implies break in both intercept and slope. * and ** indicate statistical significance at the 5% and 10% levels. The t-statistics are in parentheses in Panel C.

Source: Authors' calculations.

Table 4: Panel cointegration test of Banerjee and Carrion-i-Silvestre (2015)

Panel A: Break points					
Country	Patent-FDI	Trademark-FDI	Country	Patent-FDI	Trademark-FDI
Argentina	2000	2002	Korea	1997	2001
Austria	1994	1994	Malaysia	1999	2000
Bangladesh	1996	2006	Mexico	2008	1996
Brazil	2003	2006	New Zealand	1997	1998
Bulgaria	1996	2010	Norway	1994	2009
Canada	1998	2001	Philippines	2007	1997
Chile	2011	2002	Poland	2009	2001
Denmark	2008	2010	Portugal	1997	2003
Finland	2008	2001	Romania	2001	2009
France	2005	1998	South Africa	2005	2003
Germany	2007	2001	Spain	1993	1999
Iceland	1995	2008	Sweden	1998	2006
India	2009	2000	Switzerland	2000	2000
Ireland	1998	1993	Turkey	2001	2010
Israel	2006	2009	United Kingdom	1995	2000
Italy	2000	1996	United States	2009	1996
Japan	2003	2000	Vietnam	1998	2007

Panel B: Panel test statistics		
	Patent-FDI	Trademark-FDI
% Individual rejections at the 5% significance level	61.8%	82.3%
Panel test statistic	-5.9E+15	-1.6E+16
p-value	0.001	0.001
$\hat{r}$	12	12
$\hat{r}P$	12	12
$\hat{r}NP$	12	12

Panel C: DOLS estimation		
Dependent variables	Independent variables	Panel
Patent	FDI	0.003 (2.253)*
FDI	Patent	25.680 (1.545)
Trademark	FDI	0.005 (0.041)
FDI	Trademark	7.538 (-0.027)

Notes: The break point in Panel A is estimated using Model 5 in Banerjee and Carrion-i-Silvestre (2015). $\hat{r}$ refers to the number of common factors. $\hat{r}P$ and $\hat{r}NP$ represent the number of common stochastic trends (Parametric) and number of common stochastic trends (Non-parametric). * and ** indicate statistical significance at the 5% and 10% levels. The t-statistics are in parentheses in Panel C.

Source: Authors' calculations.

Overall, with Westerlund (2006) and Chang *et al.* (2011) having confirmed structural breaks in GDP, our results suggest the necessity of considering structural changes when studying the association between FDI and innovation. Once we establish that FDI and innovation are related, we next estimate the long-run relationship using the dynamic ordinary least squares (DOLS) model; the corresponding results are presented in Panel C of Table 3.³ Overall, our evidence indicates that when the dependent variable is *Patent (Trademark)*, the panel estimation has a significantly positive sign, showing that FDI presents a long-run positive influence on innovation.

To ensure the robustness of the cointegration relationship, we further utilize the panel cointegration test proposed by Banerjee and Carrion-i-Silvestre (2015). The results of the panel cointegration test of Banerjee and Carrion-i-Silvestre (2015) are provided in Table 4.⁴ Similarly, Panels A, B and C correspond to these break points, panel statistics and DOLS estimation. As can be seen in Panel B of Table 4, the percentage of rejecting the spurious regression ranges from 61.8% to 81.3%. Moreover, the panel test statistics constructed based on individual information also reject the null hypothesis of no integration at the 1% level of significance no matter which model is used. The results of Panel C with DOLS in Table 4 suggest that FDI exhibits a long-run positive influence on innovation when the dependent variable is *Patent* while this effect becomes insignificant when the dependent variable is *Trademark*. These results lend strong support to the argument that there is a long-run cointegrated relationship between innovation and FDI after taking structural breaks into consideration.

3.2.3 DCCE estimation

Though the long-run positive cointegrated relationship is established, the causal relationship between FDI and innovation is still unclear. We further employ the dynamic common correlated estimator proposed by Chudik and Pesaran (2015), which can deal with the endogenous problem and cross-sectional dependence, to examine the causal effect of FDI on innovation.⁵ In the estimation, we include the control variables separately, the break point variable, the economic development and population variable, and all of the control variables. It should be noted that the control variables include economic development (*Lngdpp*), openness (*Trade*), population (*Lnpop*), urbanization (*Urban*), and corruption level (*Corruption*).

3 The DOLS model is not simply fully parametric, but also combines with the leads and lags of the independent variables, offering reliable evidences for the long-run relationship. The estimated break points are included in the DOLS model.

4 To maintain consistency with Westerlund and Egerton (2008), we consider one break in the panel cointegration test.

5 We are grateful to referees for providing this advice.

Table 5: DCCE model estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent	Patent	Patent	Trademark	Trademark	Trademark
L.Patent	0.023 (0.479)	−0.191* (−2.181)	−0.417* (−4.755)	–	–	–
L.Trademark	–	–	–	0.040 (0.824)	−0.071* (−2.704)	−0.221* (−2.989)
FDI	0.013** (1.932)	0.013 (0.989)	0.031** (1.704)	0.007 (0.788)	0.010* (2.230)	0.021* (2.092)
Lngdpp	–	0.210* (4.226)	1.321* (2.589)	–	−0.125 (−0.645)	0.229* (2.783)
Lnpop	–	0.199 (0.105)	−7.170 (−1.202)	–	0.604 (0.656)	0.746 (0.300)
Urban	–	–	25.129 (0.798)	–	–	−19.854 (−1.410)
Trade	–	–	0.894* (2.001)	–	–	0.130* (4.649)
Corruption	–	–	0.119 (1.244)	–	–	−0.013 (−0.421)
BP1	0.020 (0.304)	0.004 (0.046)	0.041* (1.999)	–	–	–
BP2	–	–	–	−0.005 (−0.203)	0.006 (0.178)	−0.001 (−0.026)
N	748	748	748	748	748	748
R²	0.380	0.546	0.803	0.327	0.517	0.806
CD (<i>p</i>–value)	0.389	0.201	0.177	0.060	0.137	0.539

Notes: The *z*–statistics are in parentheses. The regression includes a constant term. CDP implies the corresponding *p*–value. * and ** indicate statistical significance at the 5% and 10% levels. BP1 and BP2 imply the break point variable estimated from the panel cointegration test of Banerjee and Carrion-i-Silvestre (2015).

Source: Authors' calculations.

Table 5 presents the results of the DCCE models. We incorporate the structural break estimated in Banerjee and Carrion-i-Silvestre (2015) as a variable into the regression. The Pesaran (2015) cross-sectional dependence (CD) test results are reported at the bottom

of Table 5. We see that all the models pass the CD test, and thereby these models cannot reject the null hypothesis of no cross-sectional dependence. Thus, the validity of the models is verified by the CD test. Moreover, the variable *FDI* is positive and statistically significant at least at the 10% level in all the models except columns 2 and 4 in Table 5, implying that FDI has a long-run positive influence on innovation regardless whether the measure of innovation is *Patent* or *Trademark*. This finding is in line with Vahter (2011), who shows that FDI can promote domestic innovation.

Table 6: DCCE model estimation: subsample results

Subsample	EU	EU	Non-EU	Non-EU
Variables	Patent	Trademark	Patent	Trademark
L. Patent	−0.210** (−1.983)	–	−0.190* (−2.643)	–
L. Trademark	–	−0.212* (−3.811)	–	−0.281* (−3.968)
FDI	0.008** (1.910)	0.013** (1.756)	0.019* (2.580)	0.005* (2.108)
Lngdpp	−0.171 (−0.282)	0.794 (1.232)	2.482* (2.411)	1.190* (2.391)
Lnpop	1.209 (0.388)	−3.835** (−1.836)	−12.374** (−1.864)	1.296 (0.374)
Urban	10.801 (0.657)	4.559 (0.580)	73.367 (0.771)	−14.060 (−0.459)
Trade	−0.296* (−2.905)	0.468 (1.622)	−0.121 (−0.292)	0.381 (1.181)
Corruption	0.049 (0.980)	0.047 (1.384)	−0.058 (−0.831)	0.004 (0.161)
N	396	396	352	352
R²	0.492	0.565	0.554	0.564
CD (p-value)	0.869	0.808	0.552	0.506

Notes: EU represents European countries, including Austria, Bulgaria, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. Symbols are the same as in Table 5.

Source: Authors' calculations.

As a robustness check, we divide our sample into an EU group (countries that are in Europe) and a Non-EU group and re-estimate the long-run influence of FDI on innovation using the DCCE models. The results for the subsamples are presented in Table 6. The variable *FDI* is positive and statistically significant at the 10% level in all the models, reflecting that FDI contributes to national innovation in both European countries and non-European countries. Therefore, the results of the subsamples exhibit strong evidence of the notion in the full sample that FDI has a positive influence on technological innovation in the long run.

4. Conclusions

Employing data from a panel of 34 countries for the period 1991–2016, this paper examines the influence of FDI on innovation by taking structural breaks into consideration in the panel stationarity test and the panel cointegration test. More importantly, we use the dynamic common correlated estimator to examine the long-run impact of FDI on innovation. Our results indicate that *FDI*, *Patent*, and *Trademark* follow a stationary trend under the panel LM unit root test with structural breaks. The results of the panel cointegration test reveal a long-run cointegration relationship between *FDI* and *Patent* as well as between *FDI* and *Trademark* when structural breaks are considered. The DCCE estimation hence indicates that FDI has a long-run positive influence on innovation both in the full sample and in two subsamples. We believe that our findings shed crucial insights into the long-run relationship between FDI and innovation and provide new evidence for research into FDI and innovation when considering potential structural changes.

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