Within and Between Panel Cointegration in the German Regional Output–Trade–FDI Nexus

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Abstract

For spatial data with a sufficiently long time dimension, the concept of 'global' cointegration has been recently included in the econometrics research agenda. Global cointegration arises when non-stationary time series are cointegrated both within and between spatial units. In this paper, we analyze the role of globally cointegrated variable relationships using German regional data (NUTS 1 level) for GDP, trade, and FDI activity during the period 1976–2005. Applying various homogeneous and heterogeneous panel data estimators to a Spatial Panel Error Correction Model (SpECM) for regional output growth allows us to analyze the short- and long-run impacts of internationalization activities. For the long-run cointegration equation, the empirical results support the hypothesis of export- and FDI-led growth. We also show that for export and outward FDI activity positive cross-regional effects are at work. Likewise, in the short-run SpECM specification, direct and indirect spatial externalities are found to be present. As a sensitivity analysis, we use a spatial weighting matrix based on interregional goods transport flows rather than geographical distances. This scheme thus allows us to address more soundly the role of positive and negative effects of trade/FDI on output activity for a system of interconnected regions.

JEL: C21, C22, C23, F43

Keywords: Global cointegration, Spatial Durbin model, Growth, Trade, FDI

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1 Introduction

The relationship between economic growth and internationalization activity is an active field of economic research at the firm, regional and national levels. Two of the central transmission channels through which trade and international investment activity (the latter typically in the form of Foreign Direct Investment, henceforth FDI) may affect economic growth and development are the existence of technological diffusion via spillovers and the exploitation of market-size effects. While the latter mechanism is closely related to the classical work on 'export-led-growth' in the field of trade theory and regional economics (see, e.g., Hirschman, 1958), the importance of technological diffusion and spillover effects has been particularly emphasized in the new growth theory (see, e.g., Barro & Sala-i-Martin, 2004, for an overview).

In seminal papers, Romer & Rivera-Batiz (1991) as well as Rivera-Batiz & Xie (1993) already hinted at the importance of knowledge spillovers in generating permanent growth effects from trade opening, while Feenstra (1990) demonstrated that, without technological diffusion, an economy will experience a decline of its growth rate after liberalizing trade. Summarizing the findings of the theoretical literature dealing with the spatial distribution of growth related to trade openness, Tondl (2001) argues that perfect integration with trade liberalization and technology diffusion may spur growth and eventually lead to income convergence among the group of participating regions/countries in an endogenous growth world. However, for the medium run, imperfect integration may lead to growth divergence or convergence among different 'clubs'. In this sense, it may be important to account for potentially different short- and long-run effects of trade on growth in a more complex empirical modelling framework.

The likely uneven evolution of economic growth due to internationalization activity across time and space is also prominently discussed within the field of new economic geography (NEG). Here, long-run spatial divergence may be the result of a concentration of economic activity in certain agglomerations. In almost all NEG models, free trade and capital movement play a key role. Whether agglomeration or dispersion forces dominate depends crucially on the underlying core–periphery pattern as well as the impact of trade liberalization on the reduction of the transaction costs and the size of agglomeration effects such as market size and economies of scale. Especially for FDI, the latter size factors are identified as key determinants across space rather than differences in saving rates as typically specified in the standard Solow model of growth. The latter neoclassical transmission channel is assumed to solely operate via capital accumulation, which takes place across space, when the capital-to-labour ratio is low and marginal products from capital investment are high. While the Solow model predicts (conditional) convergence, for models driven by market potential and increasing economies of scale, Martin & Ottaviano (1996) as well as Baldwin et al. (1998) show that along the lines of the new economic geography and growth models there might be a long-term equilibrium, which exhibits an asymmetric (divergent) location pattern.

As the discussion above shows, the interplay between economic growth and internationalization activity is a complex issue both across time and space. It is rather difficult to derive clear-cut results, given the plurality of different approaches. In this paper, we thus tackle this issue at the empirical level by analyzing the growth–trade–FDI nexus for West German federal states (NUTS1 Level) for the period 1976–2005. Our methodological approach rests on the analysis of merging the long- and short-run perspective by means of cointegration analysis, which aims to identify co-movements of the variables within and between cross-sections. The notion of a global panel co-integration approach has been recently introduced by Beenstock & Felsenstein (2010). This framework allows us to specify spatial panel error correction models (SpECM) which are able to identify short- and long-run co-movements of the variables in focus and avoid any bias stemming from spurious regressions.

From a statistical point of view, a proper handling of variables that may contain unit roots in the time dimension is of vital importance.[1] The merit of the global cointegration approach is that it aims at analyzing the consequences of spatial effects for the time series behavior of variables. That is, consider the case of two regions of which one region is heavily engaged in international trade or FDI and directly benefits from this activity in terms of output growth, e.g. through the exploitation of market potentials and technological diffusion. The second region instead is not actively engaged in trade activity but benefits from the first region's openness via forward and backward linkages, which in turn raise output for the second region, too. Thus, rather than having a stable long-run co-movement between its own level of internationalization activity and output evolution, the inclusion of a spatially lagged trade variable is needed to ensure cointegration of the second region's output level with trade and FDI activity. Moreover, apart from the importance of spatial lags in finding stable cointegration relationships for output, trade, and FDI in a time-series perspective, the method may also help to control for any cross-sectional dependence in the long- and short-run specification of the SpECM.

The remainder of the paper is organized as follows. In the next section, we give a brief overview of recent empirical contributions regarding the relationship of economic growth, trade, and international capital movement. So far, the empirical literature has

[1] Note that this paper does not address the handling of variables containing spatial unit roots in the definition of Fingleton (1999).

focused on the time-series perspective, aiming at identifying cointegration relationships and analyzing the direction of causality among the variables involved. Opening up the field of research to an explicit account of space may add further insights. Section 3 then briefly discusses the database used and presents some stylized facts at the German regional level. Section 4 presents the econometric specification used and, in section 5, we report the main estimation results for our chosen SpECM modelling framework. Section 6 performs a robustness check with an alternative spatial weighting matrix, section 7 concludes.

2 Theory and Empirics of Output–Trade–FDI Linkages

A common approach to model the likely transmission channels from trade and FDI activity to economic growth is to start from an aggregate production function framework (see, e.g., Edwards, 1998) as

$$Y_t = f(A_t, K_t, L_t) \quad \text{with} \quad A_t = f(FDI_t, TR_t, FDI_t^*, TR_t^*, \mathbf{Z}), \tag{1}$$

where Y_t denotes the aggregate production of the economy at time t as a function of capital K and labour L input, as well as the economy's stock of knowledge, or total factor productivity (A). Growth of the latter in turn is directly influenced by international sources such as FDI and Trade (TR), where "*" indicates values for spatial neighbors. Details on how to construct such spatial lag variables are given in section 4. $\mathbf{Z}$ is a vector of further domestic determinants of the economy's technological level. We use the augmented production function framework as a starting point for empirical model specification with theoretically motivated variable selection. For this particular modelling framework there is a growing number of contributions to test for its empirical validity. However, as Won & Hsiao (2008) point out, most of the recent works focus on partial, bivariate relationships rather than using a more general approach.[2] The majority of scholars finds uni- and bi-directional causality among exports and FDI on the one hand, as well as GDP on the other hand (with most applications being conducted for developing countries, see e.g. Hansen & Rand, 2006, Wang et al., 2004, as well as Makki & Somwaru, 2004).

In a recent survey dealing with the FDI-growth relationship, the OECD(2002) finds for 11 out of 14 studies that FDI contributes positively to income growth and factor productivity. A further meta-analysis of the latter literature is also presented by Ozturk (2007). The author likewise concludes that most studies find a positive effect of FDI on

[2]A similar point is made by Blomstroem et al. (2000), arguing that the beneficial impact of FDI on growth is only enhanced in an environment characterized by an open-trade regime. Thus, rather than looking for bivariate causality, a general framework including all relevant variables should be used.

growth. Among the few papers that deal with the simultaneous influence of trade and FDI on growth, Dritsaki et al. (2004) use cointegration analysis to identify the long- and short-run effects for Greece between 1960 and 2002. The authors find a stable long-run relationship among the variables and, using Granger causality tests, get evidence for a bi-directional causal relationship between exports and economic growth as well as a uni-directional effect from FDI on growth. Similar results were obtained by Ekanayake et al. (2003) for a sample of five North and South American countries between 1960 and 2001 (including Brazil, Canada, Chile, Mexico, and USA). The authors apply a Vector Error Correction Model (VECM) approach, which gives strong empirical support for trade-led growth, while the empirical evidence for (inward) FDI-led growth is mixed.

The explicit inclusion of spatially lagged variables in the analysis of the trade–FDI–growth nexus is uncommon in the current state of the art of empirical modelling. The only example is Ozyurt (2008), who estimates a long-run model for labour productivity of Chinese provinces driven by trade and FDI as well as their respective spatial lags.[3] The author finds that FDI and trade volumes have a positive direct effect on labour productivity. The results for the sample period 1979–2006 show that the geographical environment has a subsequent influence on labour productivity of a given region. Besides the spatial lag of the endogenous variable as a 'catch-all' proxy for spatial effects, FDI spillovers turn out to be of specific interregional nature. These findings give a first indication that spillovers from internationalization activity are not restricted to a direct effect, but may also influence the economic development of neighboring regions.

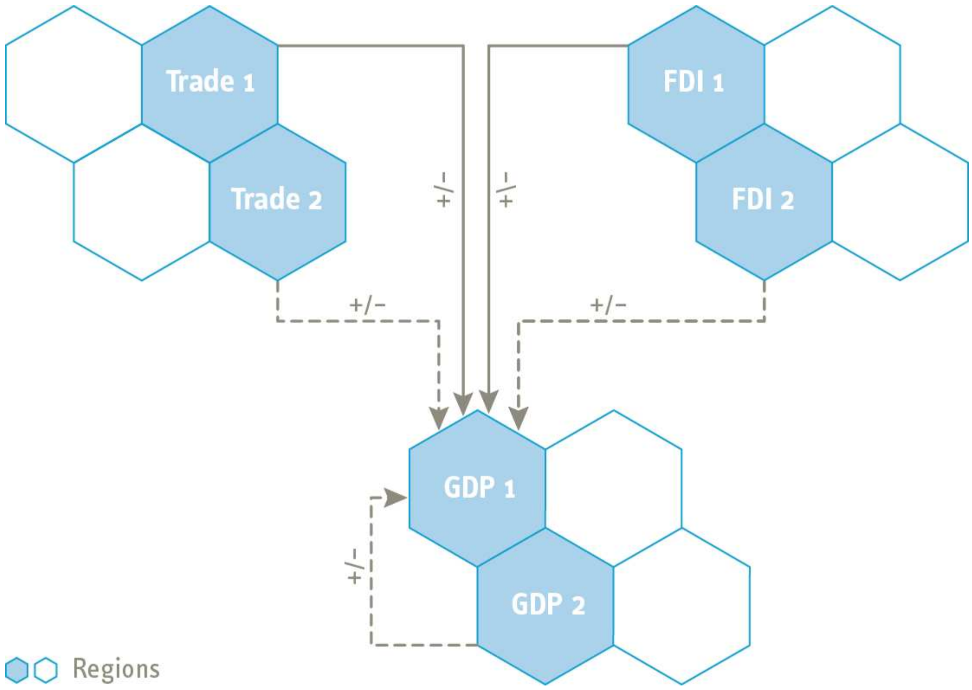
To sum up, based on the theoretical and empirical benchmark specifications, we aim to test the following hypothesis:

- *Hypothesis* 1: Trade and FDI activities are directly related through market size and intraregional technological spillover effects to the economy's output performance both in the long- and short-run ('Trade-led' and 'FDI-led' growth).
- *Hypothesis* 2: Trade and FDI activities are indirectly related to the economy's output performance through forward and backward linkages as a source of interregional spillover effects both in the long- and short-run.
- *Hypothesis* 3: Besides trade and FDI spillovers, there are also direct short-run linkages between the economic growth performance of neighboring regions, which may stem from domestic rather than international sources.

[3] Additionally, there is a growing literature with respect to third-country effects of FDI activity. See, e.g., Baltagi et al. (2007).

The different direct and indirect transmission channels from internationalization activity for the stylized case of two regions are illustrated in figure 1. Solid arrows in the figure indicate a direct relationship between regional output and the region's internationalization activity, while dashed arrows mark indirect spatial spillover effects. Note that the reduction of the system to a single equation approach with causality being assumed to run from trade and FDI to growth abstracts from the likely role of feedback effects and bidirectional causality.

Figure 1: Sources of internationalization effects on regional output



3 Data and Stylized Facts

For the empirical analysis, we use regional panel data for the 10 West German federal states between 1976 and 2005. Our data comprise GDP levels, export and import volumes, as well as inward and outward stocks of FDI. All data are used in real terms. For the analysis, all variables are transformed into logarithms.[4] As a benchmark we use a spatial

[4]It would be desirable to have a higher degree of regional disaggregation rather than $N = 10$ with $T = 30$. However, no such data on trade and FDI activity is available. The panel structure of the data is nevertheless still comparable to

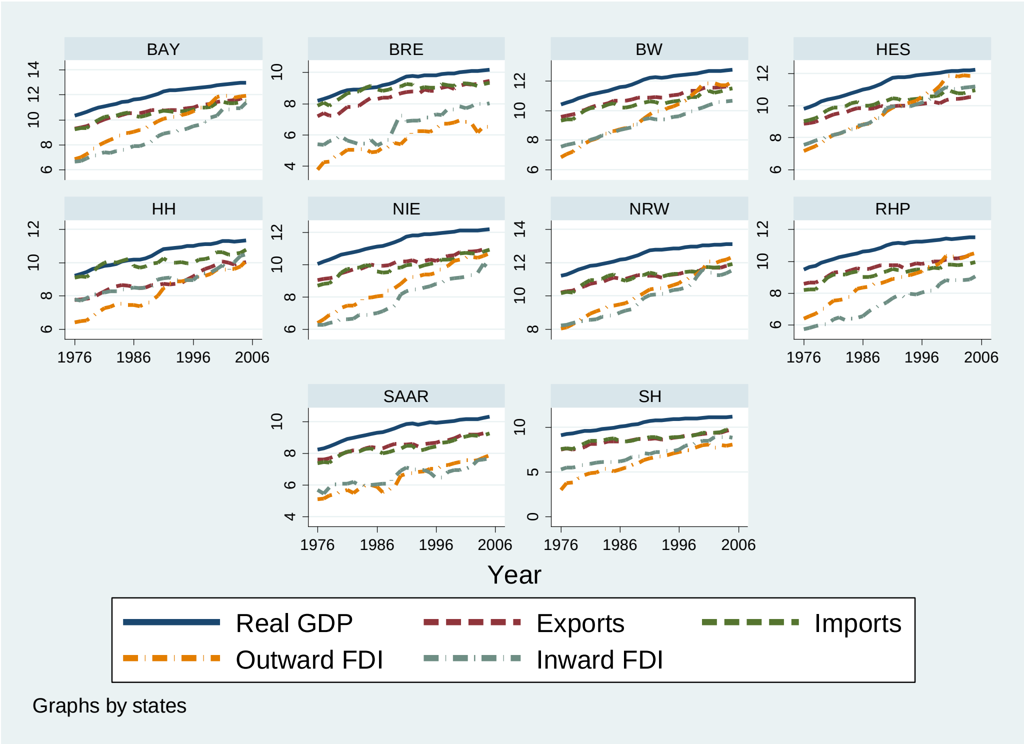
weighting scheme that contains binary information on whether two states share a common border or not. The spatial weighting matrix is used in its row-normalized form. To check for the sensitivity of the results, we also use a weighting matrix based on interregional transport flows rather than geographical information. The sources and summary statistics of the data are given in table 1. Additionally, figure 2 plots the time evolution of the variables for each West German federal state. As the figure shows, all variables increase over time. The evolution of real GDP shows the smoothest time trend, while the values for trade and FDI activities show a more volatile pattern. The figure also displays that both inward as outward FDI stocks start from a rather low level in the 1970s but increase rapidly over time. Except for the small states *Bremen* and *Saarland*, which show to have a strong trade performance, the gap between trade and FDI activity gradually decreases over time. In the following, we will more carefully account for the co-evolution of GDP and internationalization activity by means of cointegration analysis.

Table 1: Data sources and summary statistics of the variables

Variable	**Description**	**Source**	**Obs.**	**in logarithms**			
				Mean	**Std. Dev.**	**Min**	**Max**
y	Real GDP (in Euro)	VGR der Länder (VGRdL, 2009)	300	10.95	1.17	8.19	13.12
ex	Real Exports (in Euro)	Destatis (2009)	300	9.66	1.12	7.19	11.9
im	Real Imports (in Euro)	Destatis (2009)	300	9.76	1.01	7.37	11.93
$fdi\ in$	Real Stock of inward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.16	1.57	5.3	11.57
$fdi\ out$	Real Stock of outward FDI (in Euro)	Deutsche Bundesbank (2009)	300	8.32	2.03	3	12.36

Beenstock & Felsenstein (2010) with $N = 9$ and $T = 18$, so that it should be feasible to apply their proposed method to our regional data.

Figure 2: GDP, trade and FDI by German states (in logs)



Source: See table 1.
Note: BW = Baden Württemberg, BAY = Bavaria, BRE = Bremen, HH = Hamburg, HES = Hessen, NIE = Lower Saxony, NRW = North Rhine-Westphalia, RHP = Rhineland-Palatine, SAAR = Saarland, SH = Schleswig-Holstein.

As we have seen from figure 2, all variables grow over time, indicating that the variables are likely to be non-stationary. To analyze this more in depth, we therefore compute standard panel unit root tests proposed by Im et al. (2003) as well as Pesaran (2007). The latter test has the advantage that it is more robust to cross-sectional correlation brought in by spatial dependence (see, e.g., Baltagi et al., 2007), while the Im et al. (2003) test is found to be oversized, when the spatial autocorrelation coefficient of the residual is large (around 0.8). The results of both panel unit root tests are reported in table 2. As the results show, both test statistics give evidence that all variables are integrated of order I(1) and are stationary after taking first differences.

4 Econometric Specification

The estimation of I(1)-variables has a long tradition in time-series modelling and has recently been adapted to panel data econometrics (see, e.g., Hamilton, 1994, Baltagi,

Table 2: Panel unit root tests

	IPS test for N=10, T=30		CADF test for N=10, T=30	
Variable	**W[t-bar] (P-Value)**	**Av. Lags**	**Z[t-bar] (P-Value)**	**Av. Lags**
y	0.07 (0.53)	1.50	0.53 (0.70)	2
ex	-1.37* (0.09)	1.10	-1.16 (0.12)	1
im	2.69 (0.99)	0.50	-0.59 (0.28)	1
$fdi\ in$	0.56 (0.71)	1.20	-2.21** (0.02)	1
$fdi\ out$	-0.91 (0.18)	0.70	1.45 (0.93)	1
Δy	-9.27*** (0.00)	1.10	-4.51*** (0.00)	1
Δex	-13.52*** (0.00)	0.70	-7.08*** (0.00)	1
Δim	-9.85*** (0.00)	0.70	-6.83*** (0.00)	1
$\Delta fdi\ in$	-13.58*** (0.00)	0.70	-5.34*** (0.00)	1
$\Delta fdi\ out$	-9.81*** (0.00)	0.90	-3.88*** (0.00)	1

Note: ***, **, * denote significance at the 1, 5 and 10 % level. For IPS, the optimal lag length is chosen according to the AIC. H_0 for both panel unit root test states that all series contain a unit root.

2008). In this section, we expand the scope of the analysis from a within-panel perspective to a simultaneous account of between-panel linkages, leading to a more global concept of cointegration (see Beenstock & Felsenstein, 2010). To show this, we start from a spatial panel data model with the following general long-run form:

$$Y_{it} = \alpha_i + \beta X_{it} + \theta Y^*_{it} + \delta X^*_{it} + u_{it}, \tag{2}$$

where Y_{it} is the dependent variable of the model for $i = 1, 2, \ldots, N$ spatial cross-sections, $t = 1, 2, \ldots, T$ is the time dimension of the model. X_{it} is a vector of exogenous control variables; α_i is a vector of cross-sectional fixed effects, and u_{it} is the model's residual term. Both Y and X are assumed to be time-integrated of order $Y \sim I(d)$ and $X \sim I(d)$ with $d \leq 1$. If X and Y are co-integrated, the error term u should be stationary as $u \sim I(0)$. Asterisked variables refer to spatial lags defined as

$$\begin{aligned} Y^*_{it} &= \sum_{j \neq i}^{N} w_{ij} Y_{jt}, \\ X^*_{it} &= \sum_{j \neq i}^{N} w_{ij} X_{jt}, \end{aligned} \tag{3}$$

where w_{ij} are typically row-standardized spatial weights with $\sum_i w_{ij} = 1$. As Beenstock & Felsenstein (2010) point out, in an aspatial specification u_{it} may be potentially affected by cross-sectional dependence. However, the presence of spatial lags should capture these effects and account for any bias stemming from omitted variables. Further, since the spatial lags Y^*_{it} and X^*_{it} are linear combinations of the underlying data, they have the same order of integration as Y_{it} and X_{it}, respectively. For the non-stationary case, the presence of spatial lags thus enlarges the cointegration space to find long-run specifications with a stationary residual term u_{it}.

As pointed out in the seminal work of Engle & Granger (1987), cointegration and error correction are mirror images of each other. We may thus move from the specification of the long-run equation in eq.(2) to a dynamic specification in first differences, which nevertheless preserves the information of the long-run equation. The resulting (Vector) error correction model ((V)ECM) describes the dynamic process through which cointegrated variables are driven in the adjustment process to their long-run equilibrium. In the following we build on the concept proposed by Beenstock & Felsenstein (2010) and specify a spatial ECM (SpECM) as dynamic process, in which spatially cointegrated variables co-move over time. We allow for deviations from a stable long-run equilibrium relationship in the short-run. However, the 'error correction' mechanisms ensures the stability of the system in the long-run.

Therefore, the SpECM concept encompasses three important types of cointegration: (i) If cointegration only applies within spatial units but not between them, we refer to 'local' cointegration. The latter is the standard concept of cointegration with respect to (panel) time series analysis. (ii) 'spatial' cointegration refers to the case in which non-stationary variables are cointegrated between spatial units but not within them. As Beenstock & Felsenstein (2010) point out, in this case, the long-term trends in spatial units are mutually determined and do not depend upon developments within spatial units. (iii) Finally, if nonstationary spatial panel data are both cointegrated within and between cross-sections, we refer to 'global' cointegration.

The resulting SpECM associated with eq.(2) in its first-order form can be written:

$$\begin{aligned} \Delta Y_{it} &= \gamma_{0i} + \gamma_1 \Delta Y_{it-1} + \gamma_2 \Delta X_{it-1} + \gamma_3 \Delta Y^*_{it-1} + \gamma_4 \Delta X^*_{it-1} \\ &\quad + \gamma_5 u_{it-1} + \gamma_6 u^*_{it-1} + e_{it}, \end{aligned} \tag{4}$$

where e_{it} is the short-run residual which is assumed to be temporally uncorrelated, but might be spatially correlated such that $Cov(e_{it}e_{jt}) = \sigma_{ij}$ is nonzero. The terms u_{it-1} and u^*_{it-1} are the (spatially weighted) residuals from the long-term relationships of the system. The latter are stationary for the case of a cointegration system. The coefficients for u and u^* can be interpreted as error correction coefficients, which drive the system to its long-run equilibrium state. Global error correction arises if γ_5 and γ_6 are non-zero. For the nested case of local co-integration, we typically assume that $\gamma_5 < 0$ in order to restore the long-run equilibrium.

It is straightforward to see that if the coefficients for u and u^* are zero, the long-run information used for estimation drops out and the system in eq.(4) reduces to a single equation in a spatial VAR (SpVAR) formulation. Note, that in the short run, X may affect Y differently from how it affects Y in the long run. Hence, γ_2 in eq.(4) may be different from δ in eq.(2). It is also important to note that the coefficient for the time lag of the dependent variable (γ_1) is typically expected to have the same sign as the coefficient for u^* (γ_6), since the dynamics of Y will be affected by u^* among neighbors. For the case of $\gamma_5, \gamma_6 \neq 0$ the resulting SpECM specification exhibits 'global error correction'. As Beenstock & Felsenstein (2010) point out, the SpECM in eq.(4) should only contain contemporaneous terms for ΔX and ΔX^* if credible instrument variables could be specified for them or if these variables are assumed to be exogenous. The latter implies for our empirical case, that error correction runs from X to Y but not the other way around.

5 Empirical Results

5.1 Within Panel Cointegration and ECM

As shown in table 2, all five variables are integrated time series. In order to use both the information in levels as well in first differences, the variables should be co-integrated to avoid the risk of getting spurious estimation results. Several methods have been derived to test for panel cointegration (see, e.g., Wagner & Hlouskova, 2007, for a recent survey and performance test of alternative approaches). These can be classified as single-equation and system tests, with the most prominent operationalizations in time-series analysis being the Engle-Granger (1987) and Johansen (1991) VECM approaches, respectively. In this paper, we apply the Kao (1999) and Pedroni (1999) panel ρ tests as single-equation approaches in the spirit of the Engle-Granger and additionally a Fisher (1932) type test, where the latter combines the probability values for single cross-section estimates of the Johansen (1991) system approach. The Fisher-type test can be defined as

$$-2\sum_{i=1}^{N} log(\phi_i) \rightarrow \chi^2 2N, \tag{5}$$

where ϕ_i is the p-value from an individual Johansen cointegration test for cross-section i. Here, we apply the Fisher test to the maximum eigenvalue ($\chi - max$) of the johansen (1991) approach, which tests the null hypothesis of r cointegration relationships against the alternative of $(r + 1)$ relationships. This allows us to study more carefully the likely number of cointegrated variables in the system compared to residual based single equation approaches such as in Kao (1999). Depending on the results, we are then able to move on and specify different regression models which are capable of estimating non-stationary panel data models including information in levels and first differences.

Since we have rather limited time-series observations, which makes it hard to estimate individual models for each German region, a natural starting point would be to pool the time-series and cross-section data for purposes of estimation. However, this is only feasible if the data is actually 'poolable' (see, e.g., Baltagi, 2008). Among the common estimation alternatives in this setting with small N and increasing T are the pooled mean group (PMG) and the dynamic fixed effects (DFE) model. While the PMG estimator allows for cross-section specific heterogeneity in the coefficients of the short run parameters of the model (see Pesaran et al., 1999), the DFE model assumes homogeneity of short and long-run parameters in the estimation approach. Given a consistent benchmark (such as the standard mean group estimator, see Pesaran & Smith, 1995), we are also able to test for the appropriateness of the pooling approach by means of standard Hausman (1978) tests. Table 3 reports the estimation results for the PMG and DFE estimator for the panel of German Federal states between 1976 and 2005.

If we first look at the panel cointegration tests in table 3 for the five variables employed, we see that the Kao (1999) test clearly rejects the null hypothesis of no cointegration. However, using the Pedroni panel ρ test, which performed better in the large-scale simulation study of Wagner & Hlouskova (2007) compared to the Kao residual test, the evidence of a stable cointegration relationship for the variables becomes less evident. Here, we only get empirical support at the 10% significance level. Finally, looking at the p-value-based Fisher statistic for the Johansen maximum eigenvalue test also gives rather ambiguous results. While the test in first place indicates statistical support for the existence of only one cointegration relationship between two of the five variables, there is also further evidence of a stable cointegration vector including all variables (at the 5% significance level).

Regarding the estimated coefficients, the results in table 3 show that we find a positive long-run effect of export activity on growth, both for the PMG and the DFE models. This is consistent with the export-led growth theory of regional economics. However, for imports, we find a negative impact on GDP, which is, however, only statistically significant at the 10 % level. The models do not find any long-run causation from FDI activity (both inward and outward) to GDP. Looking at the short-run coefficients, we see that the coefficient of the error correction term is statistically significant and of expected sign, although the speed of adjustment to the long-run equilibrium is rather slow (around 5-6 % per year). Though we do not find a statistical long-run impact of import and FDI

Table 3: Aspatial model estimates for the growth-trade-FDI Nexus

Dep. Var.: Δy	**PMG**	**DFE**
	Long run estimates	
ex_{it}	1.02^{***}	0.78^{***}
	(0.337)	(0.299)
im_{it}	-0.42^{*}	-0.47
	(0.224)	(0.323)
$fdi\ out_{it}$	-0.21	-0.15
	(0.157)	(0.235)
$fdi\ in_{it}$	0.16	0.16
	(0.118)	(0.169)
	Short run estimates	
u_{t-1}	-0.06^{***}	-0.05^{***}
	(0.009)	(0.014)
Δy_{t-1}	0.29^{***}	0.33^{***}
	(0.048)	(0.048)
Δex_t	-0.08^{**}	-0.01
	(0.038)	(0.033)
Δim_t	0.10^{***}	0.07^{***}
	(0.016)	(0.022)
$\Delta fdi\ out_t$	0.07^{***}	0.06^{***}
	(0.019)	(0.013)
$\Delta fdi\ in_t$	0.06^{***}	0.06^{***}
	(0.012)	(0.013)
Kao (1999) ADF (p-value)	-4.23^{***} (0.00)	
Pedroni (1999) ρ (p-value)	2.01^{*} (0.06)	
$\chi - max$ of Johansen (1991) based Fisher test (p-value)		
$rank \leq 0$	115.2^{***} (0.00)	
$rank \leq 1$	50.93^{***} (0.00)	
$rank \leq 2$	24.93 (0.20)	
$rank \leq 3$	27.78 (0.11)	
$rank \leq 4$	31.64^{**} (0.05)	
Hausman Test $\chi^2(4)$ (p-value)	15.29^{***} (0.00)	0.01 (0.99)
$STMI$	5.96^{***}	7.45^{***}
p-value	(0.00)	(0.00)
p^b-value	(0.00)	(0.00)

Note: ***, **, * denote significance at the 1, 5 and 10 % level. Standard errors in brackets. The Hausman test checks for the validity of the PMG and DFE specifications against the MG estimation results. H_0 for panel cointegration tests is the no-cointegration case. For Johansen VECM-based Fisher-type test, MacKinnon-Haug-Michelis (1999) p-values are reported. $STMI$ is the spatio-temporal extension of the Moran's I statistic, which tests for H_0 of spatial independence among observations. Since we are dealing with a small number of cross-sections, we use standard as well as bootstrapped p-values of the test. The latter are marked by a "b".

activity on economic growth, there is a multidimensional positive short-run correlation from import and both FDI variables to output growth. The sole exception is export flows, for which we do not find any short-run effect in the DFE model and a reversed coefficient sign in the PMG model.

If we finally check for the appropriateness of the respective estimators, we see from the results of the Hausman m-statistic that only for the DFE model we cannot reject the null hypothesis of consistency and efficiency of the DFE relative to the benchmark mean group (MG) estimator.[5] On the contrary, the PMG is found to be inconsistent. Thus, we conclude that the DFE is the preferred (aspatial) model specification in the context of the German growth–trade–FDI nexus.

So far we did not account for the spatial dimension of the data. As Beenstock & Felsenstein (2010) point out, this may lead to a severe bias of the estimation results both in terms of the cointegration space of the variables as well as incomplete handling of spatial dependence in the model. To check for the appropriateness of our a-spatial co-integration relationship from table 3, we calculate a spatio-temporal extension to the Moran's I statistic (thereafter labeled $STMI$) for the estimated models' residuals, which has recently been proposed by Lopez et al. (2009).

Since we are dealing with a small number of cross-sections, we compute both asymptotic as well as bootstrapped test statistics to get an indication of the degree of misspecification in the model. Lin et al. (2009) have shown that bootstrap based Moran's I values are an effective alternative to the asymptotic test in small-sample settings. Details about the computation of the $STMI$ and bootstrapped inference are given in the appendix. As the results show, the $STMI$ strongly rejects the null hypothesis of spatial independence among the observed regions for both the asymptotic as well bootstrapped-based test statistic using a distance matrix based on common borders among German states. In sum, these results may be seen as a first strong indication that the absence of explicit spatial terms in the regression may induce the problem of spurious regression.

5.2 Global Cointegration and SpECM

We now move on to an explicit account of the spatial dimension both in the long- and short-run specification of the model. First, we estimate the long-run equation for the relationship of GDP, trade, and FDI. The results for different estimation strategies are shown in table 4. We start from a simple fixed effects specification. However, due to

[5] We do not report regression results of the MG estimator here. They can be obtained from the author upon request. The MG estimator assumes individual regression coefficients in the short- and long-run and simply averages the coefficients over the individuals. Pesaran & Smith (1995) have shown that this results in a consistent benchmark estimator.

the inclusion of spatial lags, OLS estimation may lead to inconsistent estimates of the regression parameters (see, e.g., Fischer et al., 2009). Since eq.(2) takes the form of a general spatial Durbin model, it may be appropriately estimated by maximum likelihood (ML), which has recently been proposed for panel data settings in Beer & Riedl (2009). The estimator of Beer & Riedl (2009) makes use of a fixed-effects (generalized Helmert) transformation proposed by Lee & Yu (2010) and maximizes the log-likelihood function with imposed functional form for the individual variances to keep the number of parameters to be estimated small (for details, see Beer & Riedl, 2009). The authors show by means of a Monte Carlo simulation experiment that the SDM-ML estimator has satisfactory small-sample properties. Besides the SDM-ML model, which includes spatial lags of the endogenous and exogenous variables, we also estimate a spatial Durbin error model (SDEM), which includes spatial lags of the exogenous variables and a spatially lagged error term as well as estimate the SDM by GMM.

Again, we first look at the obtained test results from the panel cointegration tests including spatial lags of the exogenous variables. The results in table 4 give strong empirical evidence that the estimated system is cointegrated. Compared to the aspatial specification the result of the Pedroni (1999) test is improved (statistically significant at the 1% level); the same applies to the results of the Fisher-type Johansen test. The latter statistics cannot reject the hypothesis of stable cointegration relationships between all variables. Our results can thus be interpreted along the lines of Beenstock & Felsenstein (2010), who find that the inclusion of spatial lags of exogenous variables is necessary to ensure a stable cointegration relationship for a regional economic model.

As before, we also observe a positive effect from exports on GPD in the spatially augmented long-run relationship. The estimated elasticity is somewhat smaller compared to the aspatial estimators from above. Next to the direct export effect for the DFE, we also observe an indirect effect from the spatial lag of the export variable (ex^*). That is, an increased export activity in neighboring regions also spills over and leads to an increased GDP level in the home region. The effect, however, becomes insignificant if we move from a simple FEM regression to a ML based estimator for the general spatial Durbin model (SDM) and spatial Durbin error model (SDEM) as well as the GMM approach in table 4.[6] All specifications show a significant direct effect of outward FDI on regional output. The latter can be associated with the FDI-led growth hypothesis. Additionally, the SDM-ML model also finds a significant positive coefficient for interregional spillovers from outward FDI stocks on the output level. The direct impact of import flows turns

[6]We specify the GMM approach in extension to the ML estimators, since the model may be a good candidate for estimation of the time and spatial dynamic processes in the second step short-run specification.

Table 4: Spatially augmented long-run estimates of GDP, trade and FDI

Dep. Var.: y	**Spatial FEM**	**SDM-ML**	**SDEM-ML**	**SDM-GMM**
ex_{it}	0.27***	0.49***	0.41***	0.55**
	(0.098)	(0.089)	(0.076)	(0.232)
im_{it}	0.08	-0.03	0.06	0.40
	(0.086)	(0.106)	(0.072)	(0.247)
$fdi\ out_{it}$	0.28***	0.28***	0.19***	0.36**
	(0.040)	(0.057)	(0.029)	(0.158)
$fdi\ in_{it}$	0.04	-0.01	0.06**	-0.41
	(0.037)	(0.049)	(0.028)	(0.258)
ex^*_{it}	0.19*	0.07	0.05	-0.02
	(0.101)	(0.049)	(0.078)	(0.320)
im^*_{it}	-0.20**	-0.10**	0.03	0.33
	(0.103)	(0.042)	(0.082)	(0.285)
$fdi\ out^*_{it}$	0.04	0.18***	0.04	-0.04
	(0.049)	(0.032)	(0.036)	(0.084)
$fdi\ in^*_{it}$	-0.01	-0.05*	-0.02	-0.01
	(0.048)	(0.029)	(0.034)	(0.147)
y^*		-0.23***		-0.06
		(0.021)		(0.582)
$error^*$			0.19***	
			(0.012)	
Kao (1999) ADF (p-value)	-3.70*** (0.00)			
Pedroni (1999) ρ (p-value)	2.74*** (0.00)			
$\chi - max$ of Johansen (1991) based Fisher Test (p-value)				
$rank \leq 0$	741.0*** (0.00)			
$rank \leq 1$	449.1*** (0.00)			
$rank \leq 2$	230.4*** (0.00)			
$rank \leq 3$	132.3*** (0.00)			
$rank \leq 4$	108.2*** (0.00)			
$rank \leq 5$	52.1*** (0.00)			
$rank \leq 6$	55.1*** (0.00)			
$rank \leq 7$	41.6*** (0.00)			
$rank \leq 8$	46.4*** (0.00)			

Note: ***, **, * denote significance at the 1, 5 and 10 % level. Standard errors in brackets. H_0 for panel cointegration tests is the no-cointegration case. For Johansen VECM-based Fisher-type test, MacKinnon-Haug-Michelis (1999) p-values are reported. The *SDM-GMM* uses up to two lags for the exogenous variables and their spatial lags, as well as the twice lagged value of the spatial lag of the endogenous variable.

out to be insignificant. However, we get a significant negative coefficient for the indirect spillover effect (both for the FEM and SDM-ML), indicating that higher importing activity in neighboring regions are correlated with GDP levels in the own region. For inward FDI, we hardly find any direct or indirect spatial effect on GDP.

While the partial derivatives of direct and indirect effects for each exogenous variable can be immediately assessed for the FEM and SDEM-ML results in table 4,[7] LeSage & Pace (2009) have recently shown that for model specifications including a spatial lag of the endogenous variable, impact interpretation is more complex. Table 5 therefore additionally computes summary measures for the SDM-ML based on a decomposition of the average total effect from an observation into the direct and indirect effect. The table shows that there is a significant total effect of export flows on the regional GDP level, which can be almost entirely attributed to its direct effect. Imports and inward FDI are not found to have either a significant direct or indirect effect, while for the case of outward FDI, we find both a positive direct as well as indirect effect. The latter results contrast findings from the SDEM-ML, indicating a significant effect running from inward FDI to growth. As LeSage & Pace (2009) point out, we cannot directly judge about the validity of one of the two models, since the SDEM does not nest the SDM and vice versa. However, one potential disadvantage of the SDEM compared to the SDM is that it could result in severe underestimation of higher-order (global) indirect impacts (see LeSage & Pace, 2009, for details). We may thus argue that SDM-ML is the most reliable specification for the long-run estimation of the output–Trade–FDI system.

Table 5: Direct, indirect and total effect of variables in SDM-ML

	direct	**indirect**	**total**
ex_{it}	0.52***	-0.07	0.46***
im_{it}	0.03	-0.14	-0.11
$fdi\ out_{it}$	0.21***	0.17***	0.37***
$fdi\ in_{it}$	0.03	-0.08	-0.05

Note: ***, **, * denote significance at the 1, 5 and 10 %-level using simulated parameters as described in LeSage & Pace (2009).

We then move on and use the obtained long-run cointegration relationship in a SpECM framework for regional GDP growth. The estimation results of the SpECM are shown in table 6. For estimation of the SpECM, we apply the standard DFE model, the SDM-ML from Beer & Riedl (2009), as well as the spatial dynamic GMM specification. The latter estimator explicitly accounts for the endogeneity of the time lag of the dependent variable

[7]This also holds for the SDM-GMM since the spatial lag coefficient of the dependent variable is insignificant.

by valid instrumental variables. Although the time dimension of our data is reasonably long, the bias of the fixed effects estimator may still be in order.[8] The spatial dynamic GMM estimator using an augmented instrument set in addition to the aspatial version proposed by Arellano & Bond (1991) as well as Blundell & Bond (1998) has recently performed well in Monte Carlo simulations (see Kukenova & Monteiro, 2009) as well as in empirical applications (e.g., Bouayad-Agha & Vedrine, 2010). Valid moment conditions for instrumenting the spatial lag of the endogenous variable besides the time lag are given in the appendix. The inclusion of time and spatial lags in the SpECM results in a 'time-space-simultaneous' specification (see, e.g., Anselin et al., 2007).

With respect to the included variables, all model specifications report qualitatively similar results. For the standard EC-term we get a highly significant regression parameter in the DFE- and GMM-based specification, which is of expected sign. Besides the results from the panel cointegration tests from table 4, this is a further indication that GDP and the variables for internationalization activity co-move over time in a long-run cointegration relationship, where short-term deviations balance out in the long-run. For the size of the EC-term, the spatial dynamic GMM model comes closest to values typically found in the empirical literature, with about one-fifth of short-run deviations being corrected after one year (see, e.g., Ekanayake et al., 2003). Also, the coefficient for the spatialized EC-term (u^*) is significantly different from zero in the DFE and GMM specification.

Looking at the short-run correlation between growth, trade, and FDI in table 6, we see that both direct and indirect (spatial) forces are present. As for the direct effects, the results do not differ substantially from the aspatial SpECM specification in table 3. We do not find any significant short-run effect from export activity on growth. However, all other variables are positively correlated with the latter. Looking more carefully at the spatial counterparts of these variables, we see that a higher export activity has a positive spillover effect on the output growth of neighboring regions while imports have a negative indirect effect (in line with the long-run findings). We also check for the significance of spatial lags in the endogenous variable and the error term. Here we find that there are indeed spatial spillovers from an increased growth performance in neighboring regions, a result which mirrors related findings for German regional growth analysis (see, e.g., Niebuhr, 2000, as well as Eckey et al., 2007). This result is also supported by the significant and positive coefficient for the spatial lag of the error correction variable (u^*). We do not find any sign for significant spatial autocorrelation left in the residuals of the SDM-ML and SDM-GMM using the (bootstrapped) $STMI$ test.

[8] Using Monte Carlo simulations, Judson & Owen (1999), for instance, report a bias of about 20 % of the true parameter value for the FEM, even when the time dimension is $T = 30$.

Table 6: Spatially augmented short-run estimates of GDP, trade and FDI

Dep. Var.: Δy	**DFE**	**SDM-ML**	**SDM-GMM**
u_{it-1}	-0.16***	-0.05*	-0.21***
	(0.025)	(0.033)	(0.034)
u^*_{it-1}	0.14***	-0.01	0.20***
	(0.025)	(0.012)	(0.036)
Δy_{it-1}	0.49***	0.36***	0.47***
	(0.040)	(0.099)	(0.049)
Δex_{it}	0.04	0.06	0.03
	(0.032)	(0.051)	(0.044)
Δim_{it}	0.10***	0.06	0.14***
	(0.024)	(0.047)	(0.011)
$\Delta fdi\ out_{it}$	0.09***	0.07***	0.08***
	(0.016)	(0.025)	(0.019)
$\Delta fdi\ in_{it}$	0.06***	0.06***	0.06***
	(0.012)	(0.020)	(0.011)
Δex^*_{it}	0.05**	0.01	0.02*
	(0.021)	(0.026)	(0.010)
Δim^*_{it}	-0.04*	-0.01	-0.04**
	(0.019)	(0.183)	(0.013)
$\Delta fdi\ out^*_{it}$	0.01	0.02	-0.02
	(0.009)	(0.014)	(0.018)
$\Delta fdi\ in^*_{it}$	0.01	0.06***	0.01
	(0.011)	(0.011)	(0.010)
Δy^*		0.22***	0.11**
		(0.036)	(0.044)
$STMI$	-2.85***	-1.08	-1.41
p–value	(0.00)	(0.14)	(0.08)
p^b–value	(0.00)	(0.84)	(0.12)

Note: ***, **, * denote significance at the 1, 5 and 10 % level. Standard errors in brackets.

6 Robustness Check: Transport Flows as Spatial Weights

The use of an appropriate spatial weighting matrix is a delicate issue in spatial econometrics (Elhorst, 2010). In order to check the stability of the short- and long-run results, we thus use an alternative weighting matrix, which employs interregional economic linkages based on transport flows for goods rather than geographical information. Since a total measure of interregional trade flows among German regions is not available, railway transportation statistics may serve as a proxy for the former. We use data from 1970 to ensure that the observed interregional linkages are exogenous to our estimation system (see table 7). A further motivation for using the transport-based weighting scheme is that we are able give a more straightforward economic interpretation regarding the estimation results. That is, for instance, consider a negative correlation of the neighboring regions' import performance with regional GDP evolution. Opening up for international trade in terms of increased import activity may lead to a substitution effect of interregional forward and backward linkages in Germany. Thus, regional supply from the region is substituted by its neighbors through international import flows. This, in turn, may slow down economic development in the region under study and can motivate a negative spatial spillover effect from import activity in neighboring regions of Germany.

Table 8 reports the result for the SpECM estimation for the DFE with spatial lags of the exogenous variables, the ML- and GMM-based spatial Durbin model. The results show that the parameters are rather stable with respect to the chosen estimator and the alternative specification of the spatial weighting matrix.[9] The error correction mechanism and its spatial lag are almost of equal magnitude compared to the border-based weighting scheme. Likewise, both the time and the spatial lag of regional GDP growth are important factors driving the dynamics of the model. Again, we find positive direct correlations between imports, inward FDI, outward FDI and GDP growth. Regarding the correlation of the indirect spatial coefficients, import flows exhibit a negative indirect effect, which turns out to be significant in the DFE and ML specifications. We find negative indirect effects for export and outward FDI in the ML-GMM model (at the 10% significance level). The inspection of the residuals using the $STMI$ shows both for the ML and GMM based SDM specification on average no remaining spatial dependence in the residuals (with only weak significance at the 10 % level for the bootstrap version in the SDM-GMM model). These results closely match findings for the common-border-based weighting scheme. In contrast, the DFE model still exhibits spatial autocorrelation in the residuals.

[9]This also holds for the long-run estimates, which can be obtained from the author upon request

Table 7: Interregional Railway Transportation Flows in 1970 (in 1000 tons)

From: / To:	SH	HH	NIE	BRE	NRW	HES	RHP	BW	BAY	SAAR	Total
SH	966	176	679	94	340	102	63	206	289	9	2924
HH	321	896	2297	374	933	342	118	361	747	27	6416
NIE	1303	1033	20434	1593	7288	1465	391	890	2140	3726	40263
BRE	42	61	3182	3158	1449	386	193	420	600	111	9602
NRW	2064	2191	11056	4705	102530	5114	3271	4821	7737	2064	145553
HES	195	491	958	517	1823	4512	782	942	1583	158	11961
RHP	181	177	618	231	2013	895	2337	2916	1722	1097	12187
BW	68	308	305	254	961	852	696	10853	2711	517	17525
BAY	143	468	578	364	1644	813	451	2225	19349	145	26180
SAAR	21	108	181	276	659	407	774	1471	898	7761	12556
Total	5304	5909	40288	11566	119640	14888	9076	25105	37776	15615	285167

Source: Statistisches Bundesamt, Fachserie H, R 4, Eisenbahnverkehr, 1970.

Table 8: Spatially augmented short-run estimates

Dep. Var.: Δy	DFE	SDM-ML	SDM-GMM
u_{it-1}	-0.13***	-0.12***	-0.21***
	(0.023)	(0.022)	(0.033)
u^*_{it-1}	0.12***	0.11***	0.20***
	(0.026)	(0.024)	(0.039)
Δy_{it-1}	0.52***	0.48***	0.46***
	(0.041)	(0.041)	(0.052)
Δex_{it}	0.06*	0.05	0.03
	(0.033)	(0.031)	(0.048)
Δim_{it}	0.08***	0.09***	0.14***
	(0.025)	(0.023)	(0.016)
$\Delta fdi\ out_{it}$	0.08***	0.08***	0.08***
	(0.016)	(0.015)	(0.017)
$\Delta fdi\ in_{it}$	0.06***	0.06***	0.06***
	(0.013)	(0.012)	(0.007)
Δex^*_{it}	0.01	0.01	-0.08*
	(0.035)	(0.033)	(0.037)
Δim^*_{it}	-0.07*	-0.07**	-0.02
	(0.042)	(0.039)	(0.040)
$\Delta fdi\ out^*_{it}$	0.02	0.02	-0.06*
	(0.023)	(0.021)	(0.028)
$\Delta fdi\ in^*_{it}$	0.03	0.01	0.01
	(0.023)	(0.012)	(0.030)
Δy^*		0.19***	0.25***
		(0.061)	(0.066)
Moran's I residuals	-2.325***	-0.377	-0.494
p–value	(0.01)	(0.35)	(0.31)
p^b–value	(0.00)	(0.80)	(0.06)

Note: ***, **, * denote significance at the 1, 5 and 10 %-level. Standard errors in brackets.

7 Conclusion

The aim of this paper was to analyze the role of within and between panel cointegration for the German regional output–trade–FDI nexus. While the analysis of co-movements among non-stationary variables is by now common standard, less attention has been paid to the importance of spatial lags in the long-run formulation of a regression model. Applying the concept of global cointegration, as recently proposed by Beenstock & Felsenstein (2010), enables us to estimate spatially-augmented error correction models (SpECM) for West German data between 1976 and 2005. Our results show that both direct as well as indirect spatial links between the variables matter when tracking their long-run co-movement.

Our long-run regression results give empirical support for a direct cointegration relationship among economic output and internationalization activity. In particular, export flows show a significant and positive long-run impact on GPD, supporting the export-led growth hypothesis from regional and international economics. Next to the direct effect for export flows, we also find evidence for long-run foreign investment driven growth through outward FDI. The latter variable is also found to exhibit significant positive spatial spillovers. To identify the long-run correlations we use both an ML- as well as GMM-based general spatial Durbin model specification. Importantly, the inclusion of spatial lags gives strong empirical evidence that the estimated regression system is cointegrated. Compared to the aspatial specification, the results of the Pedroni (1999) and the Johansen (1991) based Fisher test strongly supports cointegration relationsships among all variables. Our results can thus be interpreted in similar veins as Beenstock & Felsenstein (2010), who find that the inclusion of spatial lags of exogenous variables may have important implications for the stability of a cointegration relationship among variables for a regional economic system.

Regarding the short-run determinants of economic growth, we observe, for most variables in the specified spatial error correction model (SpECM), that positive direct effects are present for the German growth–trade–FDI relationship. With respect to the spatial lags, we find that a rise in the export flows in neighboring regions significantly increases the region's own growth rate, while imports show negative feedback effects. Finally, we also find positive growth relationship among German regions if we augment the model by the spatial lag of the endogenous variables. This result mirrors earlier evidence for Germany, reporting positive autocorrelation in regional growth rates. Our specified SpECM (both using ML as well as GMM with appropriate instruments for the time and spatial lag of the endogenous variable) passes residual based spatial dependence tests. For the latter, we use a spatio-temporal extension of the Moran's I statistic, for which we calculate both asymptotic as well as bootstrapped standard errors. We finally also test the stability of the results by using a different spatial weighting matrix based on interregional goods transport flows rather than geographical information. Our results hold for both spatial weighting schemes, giving strong evidence for the existence of direct and indirect effects in the German regional output–trade–FDI relationship, both in the long-run as well as dynamic short-run perspective.

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Appendix

A.1 Bootstrapping the spatio-temporal extension of Moran's I

Recently, different attempts have been made to improve statistical inference based on the Moran's I statistic to detect spatial dependence in the data. First, Lin et al. (2009 & 2010) have shown that the power of Moran's I statistic can be enhanced in small sample settings if bootstrapped test statistics are calculated instead of their asymptotic counterparts. Second, Lopez et al. (2009) have extended Moran's I to the case of spatio-temporal data. The authors label the extended version as the '$STMI$ test'. In the following, we will combine both proposals for the application in spatial panel data settings with a small number of cross-sections. We thus first sketch the $STMI$ test and then build a 'wild' bootstrap version of the test in the spirit of Lin et al. (2009).

The $STMI$ test proposed by Lopez et al. (2009) is a straightforward extension of the cross-section test. In the latter setting, Moran's I can be defined as

$$I = \frac{N}{S} \frac{\sum_{r \neq s} (y_r - \bar{y}) \, w_{rs} \, (y_s - \bar{y})}{\sum_{r=1}^{R} (y_r - \bar{y})}, \tag{6}$$

where $\bar{y}$ is the sample mean for a variable y, w_{rs} is the (r,s) element of a spatial weighting matrix W, N is the total number of cross-sections and S is a measure of overall connectivity for the geographical system. The null hypothesis of Moran's I is the absence of correlation between the spatial series y_r with $r = 1, \ldots, N$ and its spatial lag $\sum_{s=1}^{N} w_{rs} y_s$. Building upon I and a measure for its standard deviation, Moran's I statistic is shown to be asymptotically normal with (see Lopez et al. (2009) as well as Kelejian & Prucha, 2001, for details)

$$\frac{I}{\sqrt{Var\,(I)}} \sim N(0,1). \tag{7}$$

As Lopez et al. (2009) point out, it is not strictly necessary to restrict the application of Moran's I to just one time period. Starting from a model with T consecutive cross-sections with N observations in each of them, stacked in an $NT \times 1$ vector, the authors show that the spatio-temporal version of Moran's I can be computed as

$$STMI = \frac{NT}{S} \frac{\sum_{(t,s) \neq (r,k)} (y_{ts} - \bar{y}) \, w^{*}_{(t-1)T+s,(r-1)T+k} \, (y_{rk} - \bar{y})}{\sum_{ts} (y_{ts} - \bar{y})^2}, \tag{8}$$

where y_{ts} is a spatio-temporal process with $t \in Z$ and $s \in S$, where Z and S are sets of time and spatial coordinates with cardinality $|Z| = T$ and $|S| = R$, respectively. Each element w^* is taken from the following weighting matrix:

$$W_{NT}^* = \begin{bmatrix} W_N & 0 & 0 & \dots & 0 & 0 \\ I_N & W_N & 0 & \dots & 0 & 0 \\ 0 & I_N & W_N & \dots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & W_N & 0 \\ 0 & 0 & 0 & \dots & I_N & W_N \end{bmatrix}, \tag{9}$$

where the cross-section based spatial weighting matrix of order $N \times N$ appears along the main diagonal and the diagonal below the main diagonal contains the temporal weighting matrix I_N. The latter is defined as the identity matrix of order N (for further details, see Lopez et al., 2009). In a Monte Carlo simulation, Lopez et al. (2009) show that the $STMI$ test is robust to different types of distribution functions and has satisfactory finite sample properties.

Building upon the findings in Lin et al. (2009), we additionally develop a 'wild' bootstrap based test version for the $STMI$, which is implemented through the following steps:

Step 1: Estimate the residuals $\hat{e}_{it}$ as $\hat{e}_{it} = y - V\hat{\delta}$ for the spatial or aspatial estimator with regressors V and coefficients $\hat{\delta}$ (either short- or long-run specification) in focus and obtain a value for the $STMI$. Save the obtained $STMI$.

Step 2: Re-scale and re-center the regression residuals $\tilde{e}_{it}$ according to

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{(1 - h_{it})^{1/2}}, \tag{10}$$

where h_{it} is the model's projection matrix so that a division by $(1 - h_{it})^{1/2}$ ensures that the the transformed residuals have the same variance (for details, see MacKinnon, 2002).

Step 3: Choose the number of bootstrap samples B and proceed as follows for any j sample with $j = 1, \dots, B$:

- ***Step 3.1:*** According to the wild bootstrap procedure, multiply $\tilde{e}_{it}$ with $\tilde{v}_{it}$, where the latter is defined as a two-point distribution (the so-called Rademacher distribution) with

$$\tilde{v}_{it} = \begin{cases} -1 \text{ with probability } 1/2 \\ -1 \text{ with probability } 1/2. \end{cases} \quad (11)$$

– ***Step 3.2:*** For each of the $i = 1, \ldots, N$ cross-sections, draw randomly (with replacement) T observations with probability $1/T$ from $\tilde{e}_{it} \times \tilde{v}_{it}$ to obtain $\tilde{e}^*_{it}$.

– ***Step 3.3:*** Generate a bootstrap sample for variable y (and its spatial lag) as

$$y^*_{it} = V^*\hat{\delta} + \tilde{e}^*_{it}, \quad (12)$$

where $V^* = (Wy^*_{it}, y^*_{it-1}, X)$ and, for a time-dynamic specification, initialization as $y^*_{i0} = y_{i0}$. Thus, for a regression equation with a lagged endogenous variable, we condition on the initial values of y_{i0}, the exogenous variables X, and the spatial weighting matrix W.[10]

– ***Step 3.4:*** Obtain the residuals from the regression including y^* and V^*, calculate the bootstrap based $STMI^*$.

The full set of resulting bootstrap test statistics are $STMI^*_1, STMI^*_2, \ldots, STMI^*_B$. From the empirical distribution, we can then calculate p-values out of the nonparametric bootstrap exercise in order to perform hypothesis testing. There are various ways to do so. Lin et al. (2009), for instance, express equal-tail p-values for $STMI^*$ as

$$P^*(STMI^*) = 2min\left(\frac{1}{B}\sum_{j=1}^{B} C(STMI^*_j \leq STMI), \frac{1}{B}\sum_{j=1}^{B} C(STMI^*_j > STMI)\right), \quad (13)$$

where $C(.)$ denotes the indicator function, which is equal to 1 if its argument is true and zero otherwise. Then, given a nominal level of significance α, we compare $P^*(STMI^*_j)$ with α. Following Lin et al. (2009), one can reject the null hypothesis of no spatial dependence if $P^*(STMI^*_j) < \alpha$.

[10] See, e.g., Everaert & Pozzi (2007) for the treatment of initial values to bootstrap dynamic panel data processes. In the following, by default, we generate y^* based on the long-run cointegration specification, where we do not face the problem of time dynamics in the bootstrapping exercise. However, we additionally need to account for the generated error term and its spatial lag as explanatory regressors in the short-run equation.

A.2 Moment Conditions for the Spatial Dynamic GMM Model

The use of GMM-based inference in dynamic panel data models is a common practice in applied research. Most specifications rest on instruments sets as proposed by Blundell & Bond (1998). Their so-called system GMM (SYS-GMM) approach combines moment conditions for the joint estimation of a regression equation in first differences and levels. The latter part helps to increase the efficiency of the GMM methods compared to earlier specifications solely in first differences (e.g., Arellano & Bond, 1991). Subsequently, extensions of the SYS-GMM approach have been proposed, which make use of valid moment conditions for the instrumentation of the spatial lag coefficient of the endogenous variable (see, e.g., Kukenova & Monteiro, 2009, Bouayad-Agha & Vedrine, 2010). Kukenova & Monteiro (2009) have also shown, by means of Monte Carlo simulations, that the spatial dynamic SYS-GMM model exhibits satisfactory finite sample properties.

In this paper, we focus on appropriate moment conditions for the time-space simultaneous model including a time and spatial lag of the endogenous variable. Instruments can be built based on transformations of the endogenous variable as well as the set of exogenous regressors. Assuming strict exogeneity of current and lagged values for any exogenous variable $x_{i,t}$, then the full set of potential moment conditions for the spatial lag of $y_{i,t-1}$ is given by

– First differenced equation:

$$E\left(\sum_{i \neq j} w_{ij} \times y_{i,t-s} \quad \Delta u_{i,t}\right) = 0 \quad t = 3, \ldots, T \quad s = 2, \ldots, t-1, \tag{14}$$

$$E\left(\sum_{i \neq j} w_{ij} \times x_{i,t+/-s} \quad \Delta u_{i,t}\right) = 0 \quad t = 3, \ldots, T \quad \forall s. \tag{15}$$

– Level equation:

$$E\left(\sum_{i \neq j} w_{ij} \times \Delta x_{i,t} \quad u_{i,t}\right) = 0 \quad \text{for all} \quad s = 2, \ldots, T \quad \text{and} \quad t = 3, \ldots, T, \tag{16}$$

$$E\left(\sum_{i \neq j} w_{ij} \times \Delta y_{i,t} \quad u_{i,t}\right) = 0 \quad t = 3, \ldots, T. \tag{17}$$

One has to note that the consistency of the SYS-GMM estimator relies on the validity of these moment conditions. Moreover, in empirical application we have to carefully account for the 'many' and/or 'weak instrument' problem typically associated with GMM estimation, since the instrument count grows as the sample size T rises. We thus put special attention to this problem and use restriction rules specifying the maximum number of instruments employed as proposed by Bowsher (2002) and Roodman (2009).