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A Spatial Econometric Analysis of Regional Specialization Patterns across EU Regions

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Abstract

In this paper, I perform a spatial econometric analysis of the determinants of regional specialization patterns across EU regions. Spatial correlation is evident, but this is due mostly to spatial error autocorrelation. Spatial interaction caused by positive economic interdependencies might be present for a very few labor-intensive sectors, yet it is inconsistent across different spatial weights matrices. No clear, disadvantageous spatial interdependencies of specialization in the periphery or increasing core-periphery tendencies were identified.

Keywords: Regional specialization; Exploratory spatial data analysis; Spatial econometrics

JEL classification: C31; F15; F2; R12

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1. RATIONALE

Economic integration is supposed to foster specialization. However, there are various sides to specialization that might not be equally beneficial for all regions. Fears of increasing disadvantageous core-periphery tendencies have risen since Krugman's seminal 1991 study of potential agglomeration tendencies in EMU. Regional specialization and sectoral location patterns as well as the determinants of sectoral location have thus been at the forefront of regional economics over the past few years.

This study seeks to contribute to the debate through a spatial econometric analysis of the determinants and spatial interdependencies of regional specialization patterns in the European Union. First I examine the robustness of recent findings on the economic and locational determinants of regional specialization patterns, and second I study patterns of spatial interaction in regional specialization. This is important because some specific regional specialization might not be independent of that of the neighboring region. In contrast to recent studies, this investigation explicitly models and controls for spatial autocorrelation or interdependence by use of spatial econometric approaches and different spatial weights matrices. We find little evidence of significant economic spatial interdependencies that would lead to polarization or to declustering and no indication that integration was causing stronger regional specialization for specific sectors. But we generally detect spatial error autocorrelation that points to problems with regional definitions. And, importantly, we show that the OLS results on the determinants of regional specialization are robust.

Several mainly descriptive studies (Molle 1997; Walz 1999; Hallet 2002; Suedekum 2006, to name a few) investigate regional specialization; however, where they differ is with respect to the development of the level of specialization. Additionally, Stirboeck (2002a) does not find a clear trend of regional specialization levels over the 1985–1994 period, the same reporting period used here. However, the latter study detects an increasing impact of market integration on the level of regional dissimilarity, a result I expect to strengthen further. This might also influence sectoral specialization patterns, which are analyzed in the present study.

Amiti (1999), Haaland et al. (1999), Brülhart (1998), and Midelfart-Knarvik et al. (2000) go above and beyond the purely descriptive studies by focusing on explaining the concentration or location of sectors across space at the level of EU countries; Paluzie, Pons, and Tirado (2001) do the same across Spanish regions and Combes and Lafourcade (2001) across French regions. These studies confirm the significant role that market potential, human capital intensity, labor intensity, intermediate goods intensity as well as economies of scale and transportation costs play for the concentration or the location of (different kinds of) sectors. However, only Stirboeck (2002a, 2002b, 2004) and Kalemli-Ozcan, Sorensen, and Yosha (2003) have attempted to explain the level and patterns of regional specialization, which are at the focus of this study. This article builds on recent research by Stirboeck (2004) that gives insights into the determinants of regional specialization patterns. According to traditional and new trade theories, a number of economic determinants summarized below matter in explaining regional specialization patterns.

The above-mentioned study identifies locational indicators (e.g., market size or potential and core-periphery location) as very important in explaining regional specialization patterns. First, market potential exerts a significant influence: specialization in manufacturing sectors is higher in those regions profiting from higher gross regional product (GRP) levels. Second, as Stirboeck (2004) demonstrates, peripheral regions – in contrast to core regions – play a different role in attracting sectoral employment and (especially) investment. The driving forces of sectoral specialization are favorable for core regions with respect to growth-oriented market services. The greatest regional specialization in services sectors in peripheral regions is instead linked to economic activity in tourism. In addition to some of the services sectors, relative investment and employment in non-market economic activities are stronger in peripheral regions.

Economic openness (representing market integration), however, does not play a particular or consistent role in explaining relative specialization in specific sectors according to Stirboeck (2004). Neither do fixed time effects, since average specialization does not steadily increase or decrease over time. This is also evident in the descriptive analyses of the regional specialization levels and regions' sectoral specialization presented by Stirboeck (2002a, 2004).

Country-specific effects, however, are evident, especially for employment specialization: in this respect Italy differs from the other countries in that it exhibits larger relative employment shares in a number of labor-intensive sectors and smaller shares in manufacturing sectors. In the context of our spatial econometric analysis, it is now especially important to investigate whether spatial interdependencies are behind the identified spatial differences since the existence of country-specific effects and, especially, locational impacts points to potential spatial interdependencies.

Consequently, one shortcoming of recent analyses is their disregard of spatial interaction. Theory tells us that regional specialization tendencies, cross-border spillovers and specialization clusters may be highly important and spatially interdependent. The existence of increasing returns in the face of transportation costs across space are at the bottom of agglomeration tendencies and limit the inter-regional division of labor and the decentralized production to supply local demand, a point stressed by Venables (2005) in a recent overview on spatial interactions in the world economy.

The explanation of economic agglomeration has been an element of economic theory for some time. According to the polarization theories, circular and cumulative agglomeration might occur in some regions on the basis of demand and supply linkages sometimes referred to as "forward and backward linkages" (Hirschman 1958; Myrdal 1957). The "New Economic Geography" (Krugman, 1991) explains the local concentration of scale-intensive production. It is expected to be localized close to large markets where supply and demand are concentrated to minimize transportation costs. The (partial) immobility of labor (Venables 1996; Krugman and Venables 1995), however, prevents complete agglomeration and predicts a U-shaped pattern of sectoral concentration.

Forces working in the direction of *positive* spatial interdependencies can be summarized as "efficiency gains" (see Venables 2005, p. 6). Specifically, these can result from knowledge spillovers,[1] i.e., technological externalities, as well as intra-sectoral demand and supply linkages. In the case of inter-sectoral linkages, manufacturing as a whole might be clustered (see Venables 2005, p. 7). In general, we would expect such positive spatial lag dependencies, whereas the possibility of *negative* spatial interactions at the sector level is not straightforward economically.[2] They might be the result of, first, a heavily scale-intensive production that makes the decentralization of production inefficient and second, high transport costs that theoretically work against the development of one single place of production of final goods. This eventually delivers certain optimal market areas such as Lösch's hexagon market areas or Thünen's rings or crop patterns (see Lösch 1940; Thünen 1875). If these developments are combined with intra-sectoral linkages, we might, in an extreme case, be confronted with a "de-clustering" of similar production areas and thus negative sectoral spatial interdependencies.

On the one hand, ignoring these regional interdependencies in the estimates of the determinants of regional specialization patterns might lead to inefficient inference due to spatial autocorrelation effects. In an extreme case, econometric results based on traditional estimates can be misleading. On the other, it is of interests to directly address the existence of spatial interactions, i.e., economic interdependencies, as well. Therefore, this paper will examine the robustness of recent findings on the economic and locational determinants of regional specialization patterns, controlling for spatial correlation. In addition, we will also investigate the existence and kind of spatial interdependencies or interaction driving economic developments or specialization tendencies.

2. DATA AND INDICATORS

We analyze EU regions at the NUTS 2 level for the 1985–1994 period. The definition of NUTS regions is based on political or administrative criteria, not on economic criteria. Analyzing NUTS regions might not therefore give us the actual degree of specialization of economic entities. However, data on economic or functional regions are not available from official databases. Defining relevant economic regions depends on the variable or sector in question, which implies that a general definition may not be appropriate. By analyzing administrative entities instead, we can focus on the degree of specialization of

[1] For a broad discussion of the facets of knowledge spillover, see Keilbach (2000).

[2] At the product level, it is easy to imagine that in a monopolistic market, one firm delivers within a certain market area encompassing several regions while the next firm is located some distance away.

a territorial community that is authorized to implement regional policies or is the focus of regional structural programs.[3]

The maximum number of regions with sufficient sectoral investment and employment data is 56. Almost all of them are located in France (22), Italy (20), and Belgium (11). The three mono-regional countries Luxembourg, Denmark, and Ireland (which are also defined as NUTS 2 regions) are also included. Because the sum total of regional investments is not available for the 11 Belgian regions, these are excluded from the empirical analysis of investment specialization. Up to 17 distinct sectors – consistent with Eurostat's industrial classification NACE 1970 (Nomenclature des activités économiques dans les Communautés Européennes) – are contained in the REGIO database. They cover agriculture and manufactured products as well as market and non-market services.

In our analysis of the sectoral specialization patterns of the 56 regions, we focus on the regional investment and employment shares relative to a reference economy. We thus measure the specialization of gross fixed capital formation (GFCF) in relation to EU patterns (SP.GFCF.EU) as well as the specialization of employment in relation to EU patterns (SP.EMP.EU). This relative perspective is important as the absolute allocation of production across sectors does not give any information about a region's particularly high level of sectoral activity.[4]

In order to measure relative investment indices, we refer to adapted Balassa indices,[5] which reflect a given region's relative investment performance and relative employment performance. Taking the calculation of investment specialization as an example, the capital formation (I) share of the respective region s_{ij}^{I} is set in relation to the average sectoral share of EU value added r_i [6]:

[3] Regional policies have generally been applied in NUTS 2 regions since the 1961 Brussels Conference on Regional Economies (Eurostat 1999).

[4] While measures of absolute allocation are influenced by the sectoral classification, measures of relative allocation are influenced by the sectoral patterns of either the reference economy or the average pattern of the group of countries included. If the reference economy shows a very specific pattern, the relative specialization pattern of the economic entities analyzed can be biased. See, e.g., Stirboeck (2001) or Krieger-Boden (1999).

[5] This kind of specialization index was first applied by Balassa to use export data to analyze the relative export "performance" of a country and is known as the "revealed comparative advantage" index in international trade theory (see, e.g., Balassa 1989, p. 19).

[6] As sectoral investment and employment data are not in all cases as complete as we wish it to be, we had to use different but equivalent data representing the economic extent or importance of the different sectors at the EU level to calculate sectoral specialization indices. We therefore use gross value added at factor costs as the denominator when calculating the specialization indices in relation to patterns of EU averages. This way, we apply the same denominator to both specialization patterns, thus increasing their comparability.

(1) $$\text{SP.GFCF.EU}_{ij} = \frac{s_{ij}^{I}}{r_i} = \left(I_{ij} \, / \sum_i I_{ij} \right) / \left(\sum_j x_{ij} \, / \sum_i \sum_j x_{ij} \right)$$

with i (j) as the sectoral (regional) index.

If the region's investment or employment in one sector is relatively high (low) compared to the average sectoral share of EU value added, the index is greater (less) than 1.[7]

3. SPATIAL ASSOCIATION PATTERNS: REGIONAL CLUSTERS OF INVESTMENT AND EMPLOYMENT SPECIALIZATION

Geographic clusters of regions specialized in similar industries or sectors can be analyzed and described by a number of different spatial association statistics. In the following, we refer to the Moran I statistics as a measure of global spatial association (relative to the sector as a whole), as well as to the Getis-Ord statistics as a measure of local spatial association (comparing each region to the surrounding ones). The latter can be described as a decomposition of the global measure into the contributing factors of spatial association. Moran's I gives information on the spatial autocorrelation of an economic variable across the entire set of regions, i.e., its strength as well as its nature. Moran's I is positive (negative) if there is a significant clustering of similar (dissimilar) values. However, it does not differentiate between specific but different clusters and does not inform us about the clusters' locations. The Getis-Ord statistics provide us with further insights. First, they detect clusters of regions with similarly high and low values on the basis of a positive and negative Getis-Ord value, respectively. Second, they tell us which regions feature significant positive spatial correlation, thereby influencing the global measure of spatial association.

The choice of an inverse squared distance matrix to capture the structure of spatial interaction is determined by the assumption that the inter-regional influence on sectoral specialization should be decreasing with increasing distance. In order to build regional distance matrices, we use the coordinates of the administrative centers of the respective regions because we can assume them to be equivalent to economic centers in most cases.

The Moran I statistics in Table 1 show significant global spatial association for a number of sectors. Where this is the case, the spatial association turns out to be positive, i.e., regions similarly strong or weak in sectoral specialization are regionally clustered. Any negative Moran I value turns out to be insignificant. We thus find no evidence of

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[7] In a very few cases (four, to be precise), negative investments were replaced with zero investments in order to avoid problems in the interpretation and calculation of further indicators. Such negative investments are mostly due to realignments and depreciation and are always close to zero investments.

negative spatial autocorrelation induced by a significant systematic spatial allocation of dissimilar values. With respect to investment specialization, the significant positive spatial autocorrelation applies to 11 of the 17 sectors that are significant at least at the 10 percent level, but mostly at the 1 percent level: agriculture; fuel and power products; minerals and mineral products; metal products and machinery, etc.; food, beverages and tobacco; textiles and clothing; building and construction; recovery, repair, trade, lodging, and catering services; non-market services; and, finally, paper and printing products and various industries. The latter two, however, are only significant at the 10 percent level. Thus, regions with a high (low) specialization in one of the aforementioned sectors are more likely to be surrounded by regions with an equally high (low) specialization than by other regions. However, there are differences in the spatial association patterns for most sectors with respect to the regional specialization in investment and in employment. Sectors showing evidence of significant (positive) spatial autocorrelation for employment specialization, again mostly at the 1 percent level of significance, include: agriculture; chemicals industry; metal products and machinery; food industry, textiles and clothing; paper and printing industries; various industries; building and construction; recovery, repair, trade, lodging, and catering services; and other services.

TABLE 1

Moran I Statistics for Spatial Association

		GFCF	EMP
Agricultural, forestry and fishery products	AGRO	0.26^{***}	0.50^{***}
Manufactured products			
Fuel and power products	FUEL	0.19^{***}	0.00
Ferrous and non-ferrous ores and metals, other than radioactive	META	-0.05	0.04
Non-metallic minerals and mineral products	MINE	0.32^{***}	0.05
Chemical products	CHEM	0.02	0.10^{**}
Metal products, machinery, equipment, electrical goods	METP	0.11^{**}	0.18^{***}
Transport equipment	TREQ	-0.03	0.04
Food, beverages, tobacco	FOOD	0.12^{**}	0.27^{***}
Textiles and clothing, leather and footwear	TEXT	0.13^{**}	0.25^{***}
Paper and printing products	PAPE	0.09^{*}	0.28^{***}
Products of various industries	VARI	0.10^{*}	0.16^{***}
Building and construction	BUIL	0.24^{***}	0.26^{***}
Services			
Recovery, repair, trade, lodging and catering services	TRLO	0.23^{***}	0.23^{***}
Transport and communication services	TRCO	0.04	-0.01
Services of credit and insurance institutions	CRED	-0.02	0.03
Other market services	OTHS	0.03	0.40^{***}
Non-market services	NMSE	0.24^{***}	0.04

Significance level is based on calculation of 1,000 permutations.
***/**/* refers to a significance level of 1/5/10 percent.

Thus, the only sectors that similarly show significant positive spatial clustering for both factors of production are the following eight, all relatively labor-intensive sectors: agriculture; metal products and machinery; food industry; textiles and clothing; paper and printing products; various industries; building and construction; and recovery, repair, trade, lodging, and catering services. The descriptive statistics show that the regionally clustered over- (under-) proportional employment is also linked to over- or under-proportional capital formation in these sectors – however, according to the Moran I statistics, we cannot tell whether the clusters of specialized regions are geographically identical for both employment and investment.

In contrast to the spatial allocation pattern of these eight sectors, we find the chemicals industry and other market services to be marked by spatial clustering of employment, though not investments. This means that capital formation takes place uniformly across space in these two sectors while employment is especially strong or weak (which is the case for other market services) in a number of neighboring regions. We also find that some of the capital-intensive sectors such as fuel and power products, minerals and mineral products as well as non-market services[8] bring about regionally clustered over- (under-) proportional capital formation, which goes along with a uniform regional allocation of employment in these sectors. Finally, in the 1985-1994 period analyzed, some of the most important European growth sectors like transport equipment, transport and communication services or credit and insurance services provide neither evidence of a regional clustering of high investments nor of high employment. Thus, investments and employment in these sectors seem to be allocated uniformly across space.

The spatial econometric analysis in Section 4 will provide further evidence on the kind of spatial dependence and the potential existence of economic spillovers in those sectors for which we found significant regional clustering of either one or of both, investments and employment. For now, we will focus on the identification of the geographic clusters of regions specialized in the same sector. The Getis-Ord statistics (presented in Tables 2 and 3) provide evidence of local spatial association, i.e., which regions are significantly surrounded by similarly specialized regions.[9] Focusing on this measure, we can now specify which regions contribute to the global spatial association discussed above and whether the geographic clusters of specialized regions differ for investments and employment.

Employment specialization generally shows stronger local spatial association patterns than investment specialization, i.e., more regions are significantly surrounded by

[8] This broad sector can be assumed to be partly capital-intensive due to high-tech equipment, for example, used in business-consulting etc.
[9] The list of regions and their abbreviations can be found in the appendix in Table A1.

similarly specialized regions.[10] The only two exceptions are the fuel and power products as well as minerals and mineral products sectors, where investment specialization exhibits stronger spatial association. A strong similarity in geographic clusters of comparably specialized regions is evident for agriculture, metal products and machinery, food industry, textiles and clothing, various industries, paper and printing products as well as building and construction. This means that seven of the eight sectors simultaneously showing significant global spatial association according to the Moran I statistics for both employment and investment are also marked by relatively similar local spatial association patterns, i.e., regional clusters of, at the same time, over-proportional investments and employment. However, this is not the case for recovery, repair, trade, lodging, and catering services because the local spatial association patterns are different.[11]

For the other sectors that do not exhibit a strong or simultaneous global spatial association for both factors of production, the local spatial association patterns also differ, i.e., those regions marked by local spatial association are not the same for investment and for employment. We thus have evidence only of the similarity of local spatial association for investment as well as for employment for six manufacturing sectors and agriculture. This means that the spatial association patterns with respect to the two factors of production are mostly (i.e., in 10 out of 17 sectors) different. Overall, we can detect some clusters of sectoral specialization across EU regions, although they are not very striking. Southern Italian regions mostly show significant spatial association of high specialization in agriculture and building, but spatial association of low specialization for paper & printing industries, metal products and machinery, as well as the food industries. Some regions of central Italy (Toscana, Emilia-Romagna, Marche) as well as Corse form a cluster of high specialization in mineral industries; other regions of central and northern Italy (Emilia-Romagna, Trentino-Alto Adige, Fruili-Venezia Giulia, Umbria, Liguria, Marche, Toscana, and Lazio) as well as Corse in textiles. Most Belgian regions show local spatial autocorrelation of low specialization in agricultural employment and of high specialization in credit and other services as well as non-market services and paper & printing products. No other strong regional spatial autocorrelation patterns are visible.

[10] To some extent, this is also due to the fact that Belgian regions are excluded from the analysis of investment specialization. However, only eight sectors show significant regional spatial association of employment specialization for Belgian regions – with two sectors showing significant patterns for only two regions and one region, respectively.

[11] Three (six) Italian regions exhibit spatial autocorrelation of high (low) investment specialization while seven Italian regions and Corse show evidence of spatial autocorrelation of high employment specialization, in addition to 10 French regions and Ireland showing spatial autocorrelation of low employment specialization.

TABLE 2

Local Spatial Association Patterns According to Getis-Ord Statistics: Agriculture and Services Sectors

Agriculture, Forestry and Fishery		Recovery, Repair, trade, Lodging, etc		Transport and Communication		Credit and Insurance Services		Other Market Services		Non-Market Services	
GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP
Spatial Association of High Values											
PUG	PUG	VEN	LOM	CRS	LOM	LOR	LUB		IRE	MPY	LUX
CAL	SIC	ERO	CRS	ABR	CRS	CHA	ANT		HAI	AQU	VBR
CAM	CAL	LOM	PIE	LOM	PIE	ALS	BWA		CHA	AUV	HAI
SIC	BAS		VEN	SAR			HAI		DEN	RAL	NAM
BAS	CAM		SAR				LOR		ANT	POI	LIM
MAR	MOL		ERO				DEN		CTR	LIS	ANT
LAZ	SAR		UMB				CHA		PIC	PAC	
	LAZ		LIG				OVL		NAM	IRE	
							VBR		LIM		
							IRE		VBR		
									NPC		
									OVL		
									BWA		
									BRU		
									HNO		
									LRO		
									MPY		
Spatial Association of Low Values											
PAC	WVL	MOL	AUV				PUG	TOS	ERO	LAZ	LOM
MPY	VBR	SIC	CHA				CAL	LOR	VEN	VEN	FVG
AUV	BRU	PUG	LIS				SIC	LOM	UMB	ERO	VAO
LRO	BWA	CAM	BRT					VEN	FVG	TOS	TAA
CTR	LIE	BAS	HNO						LAZ	FVG	LIG
IRE	ALS	CAL	BNO						CAL	CRS	
PIC	LIM		AQU						BAS	TAA	
DEN	NAM		POI						CAM	ABR	
CHA	OVL		CTR						MAR	UMB	
	NPC		IDF						PUG	MAR	
	ANT		IRE						SIC		
	PIC										
	IRE										
	HAI										
	CHA										
	DEN										

Regions are shown if they indicate positive spatial autocorrelation at the 5% level of significance. GFCF (gross fixed capital formation) represents relative specialization in investments and EMP specialization in employment.

TABLE 3

Local Spatial Association Patterns According to Getis-Ord Statistics: Manufacturing Sectors

Fuel and Power Products		Ores and Metals		Minerals and Mineral Products		Chemical Products		Metal products, Machinery, Equipment, etc		Transport Equipment		Food, Beverages, Tobacco		Textiles, Clothing, Leather, etc		Paper and Printing Products		Various Industries		Building and Construction	
GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP	GFCF	EMP
Spatial Association of High Values																					
SIC	LIE	HNO	LUB	MAR	ERO	BNO	BRU	TAA	BOU	BOU	BOU	IRE	IRE	ERO	ERO	POI	IRE	RAL	TAA	PUG	PUG
CAL	ALS	IRE	ALS	TOS	MAR	IDF	IDF	LIG	VAO	CAM	IRE	PDL	PDL	TAA	UMB	BNO	DEN	TAA	RAL	SIC	SIC
CRS			LOR	ERO	TOS	NPC	DEN	VAO	IDF	VAO	BNO	NPC	IDF	FVG	FVG	PIC	BRU	VEN	FVG	CAL	CAL
PUG			CHA	CRS	CRS	PIC	PIC	BOU	TAA		VAO	IDF	BRT	LIG	TAA	IDF	CTR		VEN	CAM	SAR
BAS			DEN	LAZ			VBR	TOS	LIG		CTR		BNO	UMB	MAR	IRE	PIC			SAR	CAM
CAM			NAM	UMB			BNO		AUV				HNO	MAR	TOS	AQU	NAM			BAS	BAS
				FVG			NAM						DEN	CRS	LAZ		HAI				
				TAA			IRE						LIS		LIG		VBR				
				VEN											CRS		IDF				
																	ANT				
																	CHA				
																	HNO				
																	BNO				
Spatial Association of Low Values																					
HNO				BNO				CAL	CAM			SIC	ERO	MPY		PUG	CRS	SAR		HNO	OVL
CHA				POI				BAS	BAS			CRS	MOL			SAR	CAM			CTR	BWA
RAL				CTR				PUG	CAL			SAR	PIE			BAS	PUG			PIC	ANT
IRE				IRE				SAR	PUG				BAS			CAL	BAS			CHA	HAI
DEN								SIC	SAR				LOM			SIC	SAR			IRE	IRE
									SIC				UMB				CAL			DEN	DEN
													PUG				SIC				
													CAL								
													SAR								
													SIC								
													CRS								

Note: See Table 2

In addition, it is never the case that a significant regional cluster of over-proportional employment is linked to a regional cluster of under-proportional investment, and vice-versa. Thus, investment (employment) in a sector is always also taking place in those regions specialized in sectoral employment (investment), albeit to an average extent; and we find no evident signs of changing specialization in the 1985-1994 period. The strength of regional specialization in either employment or investment for a sector, however, also seems to be determined by the sector's capital or labor intensity in some cases. For example, regional concentration of high investment in fuel and power products or minerals and mineral products is due to natural conditions that can only be exploited by the strong capital input, which again does not point to changing specialization patterns.

In summary, we find significant global spatial association in a number of sectors, in either investment or employment or both, and will analyze potential spatial interdependencies below. However, spatial association is not general, especially not across many manufacturing sectors where we would expect supply and demand linkages to foster agglomeration tendencies. Importantly, local spatial association patterns of a given sector are, in most cases (besides six manufacturing sectors and agriculture), not alike for both employment and investment. This might imply different locational reactions for labor-intensive and capital-intensive production of one sector – which, however, cannot be investigated further with the sectoral aggregation at hand.

4. SECTORAL SPECIALIZATION: COMPARING THE PATTERNS OF INVESTMENT AND EMPLOYMENT SPECIALIZATION

4.1 Theoretical Background: the Specification

The extent of investment and employment specialization is explained – in separate estimates – by determinants of specialization patterns from traditional and new trade theories as well as regional economic theories (chiefly polarization theories). There are also recent comprehensive theoretical approaches such as Midelfart-Knarvik et al. (2001) that unite comparative advantage and geographical distribution of demand and eventually also motivate the analysis of the determinants discussed below.

In *traditional trade theory*, productivity and factor cost differentials between regions are important in explaining comparative advantages. Regions with abundant employment might specialize in labor-intensive sectors; regions relatively well-endowed with capital might focus on capital-intensive production. Thus, regional dissimilarities are based on unevenly distributed but exogenous factor allocations or technology differences. Polarization theory and the "New Economic Geography" alike attach great importance to the location of a region. Polarization theory is based on cumulative agglomeration tendencies in the center and predicts backwash effects for peripheral regions. The strong and detrimental specialization of peripheral regions combined with a beneficial specialization of central regions, might be a sign of backwash effects. A strong specialization of the central regions in the important growth-oriented sectors would support the hypothesis of the *polarization theory* of potential cumulative agglomeration in the center. The *New*

Economic Geography (NEG) emphasizes the importance of market size in explaining the location of sectors, i.e., it predicts that scale-intensive sectors concentrate production close to large markets. As long as sectoral location and regional specialization go hand in hand, determinants such as scale intensity and market size also might be important in explaining regional specialization. In addition, the NEG stresses that industries profiting from forward and backward linkages are likely to locate close to economic centers that are marked by strong demand or supply. Consistent with this, we assume that most important economic regions have disproportionately high employment or investment in those sectors. We expect the impact of market integration on the level of regional specialization to increase according to both traditional trade theory and the NEG. However, we do not know which sectors, if any, profit from market integration. Analyzing the role of economic openness for regional specialization might thus tell us which sectors, if any, are particularly influenced by increasing economic openness.

The specification we use to analyze spatial autocorrelation in the investment and employment specialization patterns is based on the specification introduced by Stirboeck (2004). However, we omit sectoral explanatory variables due to their restricted regional availability as well as R&D intensity due to the short time period of available data. The location of a region in the economic center[12] (CENTR) and the periphery (DIST) as well as the population density (PODEN) serve as locational explanatory variables that capture the impact of central location that is not simultaneously captured by CENTR. In addition, market potential proxied by gross regional product (GRP) is important in explaining specialization in scale-intensive sectors in the core regions. Economic openness, captured by an index constructed by Quinn (1997) on the basis of restrictions documented by the IMF (QUINN_OPENN),[13] is the trigger of specialization in most trade theories. However, an analysis of it might reveal which regions are particularly affected by market integration. Finally, the regional geographic size (AREA) (controlling for the potentially higher diversification of larger regions) as well as the unemployment rate (UEWP) (approximating the regional economic performance, one key determinant of investment decisions) are added as further regional control variables. However, despite their significance in the analysis presented by Stirboeck (2004), the relevant regional labor costs and sector-specific productivity levels as comparative advantage variables as well as the economies of scale variable are not used in this analysis because they are not consistently available across the whole dataset.

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[12] Approximatively, we refer to the administrative center to capture the impact of the economic center, which is a good procedure in the countries analyzed.

[13] This index varies from 0 to 14 in 0.5 steps. For further details on the evaluation of specific restrictions, see Quinn (1997). Although the index is only at the country level, the advantage of Quinn's index is its accuracy and thus its concreteness and its variation over time. Due to the high degree of integration already attained by EU countries, the yearly values for the observation points included in our analysis do not vary across the whole range of 0 to 14, but lie between 10 and 14. Since they vary in steps of 0.5 over time (e.g., between 10.5 and 14 for Italy and 11 and 13 for France over the 1985-1994 period), the inclusion of the openness index adds a dimension that differs clearly from pure country effects.

We have thus included most of the important determinants that explain specialization patterns in Stirboeck (2004) and test the following specification for each sector in a pooled regression.

$$\text{SP.GFCF(EMP).EU}_{ij} = \beta_0 + \beta_1 \text{CENTR}_j + \beta_2 \text{PODEN}_j + \beta_3 \text{DIST}_j + \beta_4 \text{GRP}_j + \beta_5 \text{QUINN\_OPENN}_j + \beta_6 \text{AREA}_j + \beta_7 \text{UEWP}_j + \text{country dummies} + \varepsilon_{ij} \quad (2)$$

with $i(j)$ as the sectoral (regional) index. Since time-fixed effects are mostly insignificant, we pooled the available observations and omitted the time index in the above specification. However, we included indicator variables for the different countries (DUM_FRA, DUM_LUX, etc.) to capture country-specific impacts. Additional explanatory variables of interest to the question in focus would include indicators on regional climate, quality of soil, and the existence of a coastline because these strongly influence natural conditions. However, their inclusion would increase the number of indicator variables even further. Depending on the data availability for sectoral investments (employment), regressions are run for up to 45 (56) regions and up to 10 years (1985 to 1994).

Because we are dealing with regional data and analyzing the process of regional specialization, we cannot – as outlined above – exclude potential correlations or interactions between regional developments. Some specific regional specialization might not be independent of that of the neighboring region. Spatial econometric approaches[14] explicitly model and control for spatial autocorrelation or interdependence to avoid inefficient or inconsistent parameter estimates or specification errors.

4.2 Controlling for Spatial Correlation and Interaction in the Analysis of Investment Specialization Patterns

In a first step, we refer to test diagnostics examining a potential spatial correlation structure in the residuals of classical, non-spatial OLS regressions by using the inverse squared distance matrix already discussed above. In order to test for robustness, the tests and estimates were additionally conducted by means of a neighborhood contiguity matrix that is one for the 10 nearest neighbors and thus assumes spatial interaction with 10 surrounding regions.[15] In quite a number of cases, we cannot accept the null hypothesis of a significant normal distribution of the error terms. As a consequence, the test diagnostics on spatial autocorrelation should only be interpreted as an indicator of the potentially

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[14] For detailed descriptions of spatial econometric tools, see e.g., Baltagi (2002), Anselin (1988), and Anselin andFlorax (2003).

[15] One common procedure is also to iterate or vary the spatial weights matrix in order to identify the matrix that gives the best fit for a particular specification. However, neither of the two spatial weights matrices used in this analysis provides evidence of its superiority across all sectors. We may therefore assume that there is not one optimal spatial weights matrix for all sectors.

underlying structure of spatial correlation because they are not as reliable as in the case of normally distributed residuals.

The Moran I test investigates the existence of all kinds of spatial correlation, while the Lagrange Multiplier (LM) error and lag tests check for the significance of a specific kind of spatial structure. Table 4 presents the results of all three tests for the analysis of the determinants of sectoral investment specialization for each of the 17 sectors. We can see that in many cases a significant structure of spatial correlation exists. The significance is not consistent in the analysis of transport equipment and chemicals as well as transport and communication services and is only very weak for various industries. The sectoral specialization of the regions analyzed seems to underlie a positive spatial correlation in some sectors (AGRO, MINE, VARI, BUIL, TRLO, CRED, OTHS) and a negative one in other sectors (FUEL, META, METP, FOOD, TEXT, PAPE, NMSE) according to the inverse squared distance matrix. The correlation structure often has a different sign when referring to the alternative spatial weights matrix.[16] In the case of spatial error correlation, the sign of the correlation structure is irrelevant for economic interpretation. And the fact that the sign varies indicates that we might not face economic spillovers (represented by spatial lag dependence) across space.

If we examine the specific kind of spatial correlation, we note that it is mixed as well (see Table 4). For most sectors, the LM tests for spatial structure are significant for both the spatial error model and the spatial lag model. Since both LM tests are sensitive to the alternative form of spatial structure, we refer to the higher value of the LM test in order to get an indication of the better specification according to Anselin (1992).[17] For nine sectors, the LM tests provide evidence that the spatial error model is the better specification. Only two services sectors (credit and insurance services and other services) show positive spatial autocorrelation of the error terms, whereas it is negative for the other seven sectors.

For five sectors (agriculture; mineral products; various products; building and construction; and recovery, repair, trade, lodging and catering services) the tests show a higher value for the LM lag test. For all of these sectors, the tests consistently point to a positive spatial lag dependence. In economic terms, this would imply that the sectoral specialization of a region in one of these sectors positively influences the specialization of the neighboring regions in the same sector.

Table A4 in the appendix compares the results of the OLS estimates with those of the ML estimates of the spatial error and the spatial lag model for each sector. First, in those cases with higher LM error test values, the spatial error model is generally confirmed to

[16] Results are available from the author upon request.

[17] The more specific "robust LM tests," which are robust against the alternative form of spatial structure, do not provide further evidence on the true structure of spatial correlation in our estimates. We do not include their results here, but instead refer to the standard tests.

be the best model either according to the insignificant spatial lag parameter or to the lower AIC value.

Second, in those cases where LM lag test values are higher, the results of the ML estimates differ. Most notably, the AIC (and/or the likelihood ratio test value) indicates the superiority of the spatial error model formulation for agriculture as well as building and construction sectors, which show a positive spatial correlation structure. In addition, the positive spatial lag dependence is weak only for various products. But finally, as predicted by the OLS test diagnostics on spatial autocorrelation, the spatial lag model shows a positive spatial dependence for the sectoral specialization in minerals and mineral products as well as in recovery, trade, repair, lodging, and catering services. Referring to the spatial neighborhood contiguity matrix, however, the spatial lag dependence is only slightly superior for the fuel and power products sector.

Finally, again referring to the inverse squared distance matrix, the spatial parameters are insignificant – as we expected according to the OLS test diagnostics – in

TABLE 4

Regression Diagnostics for Spatial Autocorrelation of Investment Specialization (Inverse Squared Distance Matrix)

	Moran I	LM error test	LM lag test
Agricultural, forestry and fishery products	4.3***	4.0**	17.3***
Manufactured products			
Fuel and power products	-8.2***	31.8***	5.8**
Ferrous and non-ferrous ores and metals, other than radioactive	-14.2***	89.9***	48.0***
Non-metallic minerals and mineral products	10.3***	33.8***	53.9***
Chemical products	1.7*	0.2	0.7
Metal products, machinery, equipment, electrical goods	-17.4***	133.3***	20.3***
Transport equipment	1.2	0.0	0.0
Food, beverages, tobacco	-13.2***	80.2***	6.8***
Textiles and clothing, leather and footwear	-8.5***	35.3***	11.9***
Paper and printing products	-3.2***	7.1***	1.2
Products of various industries	1.8*	0.2	6.3**
Building and construction	4.1***	3.6*	16.4***
Services			
Recovery, repair, trade, lodging and catering services	10.1***	32.7***	62.4***
Transport and communication services	-1.2	2.0	6.4**
Services of credit and insurance institutions	6.4***	11.4***	6.7***
Other market services	10.5***	35.4***	12.9***
Non-market services	-11.6***	57.0***	6.3**

the estimates for chemicals (the spatial lag parameter is only significant at the 10 percent level while the specification is not confirmed by the LM lag test) and for transport equipment. The spatial error model is highly significant for the transport and communication services sector, for which the classical estimates residuals provide an insignificant Moran I value even though numerous coefficients included in the specification are no longer significant. Since this is the only case with evident changes in the significance of the explanatory variables, this points instead to a misspecification of the spatial error model for transport and communication services.

To summarize, the spatial autocorrelation is insignificant in the estimates for chemical products and for transport equipment and not convincing for transport and communication services. For most other sectors, the regional specialization exhibits spatial error autocorrelation that is negative in five cases but positive in the other five cases, albeit dependent on the spatial weights matrix used. We might be confronted with a spatial lag dependence; however, this is inconsistent across spatial weights matrices in the regional specialization in these sectors: recovery, repair, trade, and lodging; various products; minerals and mineral products; and fuel and power products. Apart from these four sectors, we definitely find no spatial interdependence between the sectoral specialization of neighboring regions. The underlying spatial error autocorrelation points instead to potential data problems or to inadequate regional classifications, a fact underlined by the weights matrix-induced change in the sign of the spatial autocorrelation structure when analyzing many sectors.

Finally, if we check the sensitivity of the results of traditional OLS estimates, we find no general problem of significance concerning the non-spatial parameters. The explanatory variables that are significant in the OLS estimates are usually also significant in the spatial estimates without changing their signs. Thus, the specialization patterns discussed in Stirboeck (2004) are robust even when controlling for spatial autocorrelation effects.

4.3 Controlling for Spatial Correlation and Interaction in the Analysis of Employment Specialization Patterns

The test diagnostics on spatial autocorrelation provide evidence of a spatial autocorrelation in the OLS estimates of employment specialization for most of the sectors. As for the estimates on investment specialization, the Moran I test is mostly significant – except for building and construction and other services. Again, the significance of the spatial autocorrelation structure is very strong across all those sectors. According to the inverse squared distance matrix, we now only find five sectors (AGRO, TEXT, PAPE, VARI, and NMSE) with a significant positive spatial autocorrelation while 10 sectors (FUEL, META, MINE, CHEM, METP, TREQ, FOOD, TRLO, TRCO, and CRED) show a significant negative spatial autocorrelation structure. However, if we use the neighborhood distance contiguity matrix, the spatial autocorrelation structure given by the Moran I test is always significantly positive. As is the case for investment specialization, the inconsistency of the test statistics' sign does not convincingly prove spatial dependence in regions' sectoral specialization.

Referring to the LM tests to gain insights into the specific form of spatial autocorrelation that is present when using the inverse squared distance matrix, the LM lag test value is again mostly lower than the LM error test value. It is only higher with respect to agriculture, paper and printing products, various industries, and non-market services. It is also highly significant for building and construction as well as other services, while the Moran I tests and the LM error tests are insignificant for these two sectors. Thus, the aforementioned six sectors might be subject to significant spatial interdependencies, which need to be checked through careful discussion of the spatial estimate results.

We find significant spatial autocorrelation in the residuals of the estimates of all sectors when analyzing employment specialization, but investment specialization proved not to be affected by spatial correlation at all for three sectors. For the 11 sectors in which LM error test values exceed LM lag test values, we can confirm a significant and consistent spatial error autocorrelation. It is negative for all of those sectors save textiles.

TABLE 5

Regression Diagnostics for Spatial Autocorrelation of Employment Specialization (Inverse Squared Distance Matrix)

	Moran I	LM error test	LM lag test
Agricultural, forestry and fishery products	15.5***	71.5***	209.2***
Manufactured products			
Fuel and power products	-4.9***	12.9***	4.9**
Ferrous and non-ferrous ores and metals, other than radioactive	-17.4***	118.3***	12.9***
Non-metallic minerals and mineral products	-4.9***	13.0***	6.8***
Chemical products	-3.9***	9.1***	0.5
Metal products, machinery, equipment, electrical goods	-4.9***	13.4***	2.4
Transport equipment	-16.9***	115.6***	41.1***
Food, beverages, tobacco	-13.7***	77.8***	7.1***
Textiles and clothing, leather and footwear	21.6***	143.3***	129.2***
Paper and printing products	3.9***	2.5	10.0***
Products of various industries	13.8***	55.5***	70.4***
Building and construction	-0.7	1.3	36.6***
Services			
Recovery, repair, trade, lodging and catering services	-18.6***	137.9***	82.5***
Transport and communication services	-15.5***	98.3***	18.9***
Services of credit and insurance institutions	-11.6***	57.9***	13.6***
Other market services	-0.1	0.6	16.1***
Non-market services	5.0***	4.6**	55.5***

With respect to those six sectors under consideration for spatial lag dependence according to the inverse squared distance matrix, the identification of the optimal model is less clear. It seems that the spatial error model is superior in the analysis of paper and printing products as well as non-market services. However, it is inferior when investigating products of various industries; other market services; and building and construction as well as agricultural, forestry, and fishery products according to the AIC value (see Table A5).[18] While the Moran I statistics were insignificant for building and construction as well as other services, we now find a significant positive spatial dependence. Thus, all four sectors for which the spatial lag dependence model turns out to be superior seem to have a positive spatial lag dependence. In economic terms, this would imply that regions benefiting from high employment specialization in the products of various industries, other services, building and construction, or agriculture might exert a positive impact on the specialization of surrounding regions in this sector. However, in all of these cases the analysis with the neighborhood contiguity matrix does not confirm the spatial lag dependence.[19] As is the case for investments, results concerning spatial interdependencies are thus inconsistent across different spatial weight matrices. While the use of the inverse distance matrix would point to economic spillovers causing spatial lag dependence in four sectors, we are confronted with simple spatial error correlation applying the alternative weight matrix. This leaves us with contradictory outcomes.

Again, the use of the inverse distance matrix implies stronger identification of spatial lag dependence in comparison to the use of the neighborhood contiguity matrix for the 10 nearest neighbors: in the case of SP.GFCF.EU, three sectors in contrast to one sector; in the case of SP.EMP.EU, four in contrast to zero sectors show significant spatial lag dependence with respect to the inverse distance matrix and the neighborhood contiguity matrix, respectively. The inverse distance matrix incorporates the influence of any region, its weight decreasing with increasing distance; the influence implemented according to a neighborhood contiguity matrix cuts off at a certain limit, in our case the eleventh nearest region. It is possible that such a cut-off is too strong an assumption to capture all economic spillovers sufficiently; however, the use of the inverse distance matrix might also overestimate the influence of the surrounding regions.

However, importantly, the results of classical econometric estimates are again mostly robust when controlling for spatial autocorrelation effects. Though we have some changes in the significance of the coefficients (in both ways, either gaining or losing significance), the general results of the recent studies summarized in the first section can be confirmed.

[18] In addition, in all those cases, the likelihood ratio test value – checking for the fit of the estimated model – is much higher for the spatial lag model than for the spatial error model.
[19] Results are available from the author upon request.

5. ECONOMIC IMPACTS OF SPECIALIZATION PATTERNS AND DETERMINANTS

The spatial econometric estimates presented above allow us to draw conclusions with respect to two main topics: the robustness of the results using classical econometrics and the spatial interaction impacts on regional specialization patterns.

First, we find significant spatial autocorrelation effects for most sectors – irrespective of the results of the analysis of investments and employment. However, these do not influence the results on the economic determinants of sectoral specialization of EU regions, which can thus be assumed to be robust.

The economic determinants identified throughout this analysis differ only slightly when comparing investment and employment specialization. However, in a related study (Stirboeck 2004), some differences are evident when analyzing research intensity as well as comparative advantage variables such as labor cost or productivity differentials. As mentioned above, however, we did not include these (undoubtedly important) explanatory variables in the present analysis due to their restricted availability across time and across regions. Stirboeck (2004) demonstrated that with respect to many sectors, productivity differentials and average regional labor cost differentials as well as research intensities contribute to the explanation of regional specialization patterns in accordance with traditional trade theory. For productivity differentials, this is especially the case with respect to the explanation of investment patterns, whereas regional labor cost differentials and research intensities contribute mainly by explaining employment patterns. The explanation of part of regional specialization patterns by comparative advantages according to trade theory is in line with a uniform allocation of total production across space.

With regard to the variables in *this* study, relative investment and employment shares in manufacturing sectors are higher close to large markets but not in the administrative centers. The strength of specialization in manufacturing is influenced positively by the market potential of a region (its level of GRP) and negatively by being located in the periphery. This implies that we might be confronted with negative backwash effects for peripheral regions in scale-intensive manufacturing sectors. This is all the more valid since the regional sector-specific economies of scale are, according to Stirboeck (2004), relevant in explaining manufacturing specialization, entailing a further agglomeration potential for scale-intensive sectors.

Although market integration might have been a trigger for further agglomeration, it does not play a particular role for specific sectors. Moreover, we are not confronted with complete agglomeration of one or some sectors. Since the level of specialization is significantly lower in economic centers and large markets (see Stirboeck 2002a), we do not find a concentration of scale-intensive manufacturing sectors in just a very few regions; instead, we see that they are more or less evenly distributed across all centrally located regions. Demand and supply linkages are evidently not so strong as to lead to the complete agglomeration of whole sectors in one or few regions. This is also reflected (especially for the manufacturing sectors) in, for most, sectors the insignificant or weak (and not robust) spatial lag dependence we identified.

Country-specific effects remain relevant and are not totally captured by the economic and regional determinants discussed so far. However, only the analysis of employment specialization patterns points to clear country-specific effects: while Italy has lower employment shares in many manufacturing sectors, it has higher shares in the labor-intensive sectors of agriculture as well as recovery, repair, trade, lodging, and catering. Indeed, the latter sector might possibly be characterized by spatial interdependence, which is discussed further below. However, this interdependence might be influenced to a large extent by natural conditions such as Italy's coastline and favorable climate and less by economic interactions.

In addition to the lower specialization in manufacturing of Italian regions, peripheral regions exhibit manufacturing shares that are below the EU average. Consistent with this is their higher specialization in the services sectors. Such a stronger specialization in services is similarly evident for peripheral regions and administrative centers alike. However, the quality of specialization is where the differences lie, especially as regards investments. Growth-oriented services sector specialization (chiefly credit and insurance services as well as transport and communication services with respect to investment specialization) is more pronounced in administrative centers while tourism-related services sector specialization is stronger in peripheral regions. However, spatial interaction is not really relevant, as we will summarize in the following.

Second, spatial autocorrelation, though present, is due mostly to spatial error autocorrelation. This is the case for a large number of sectors (FUEL, META, CHEM, METP, TREQ, FOOD, TEXT, PAPE, TRCO, CRED, and NMSE) – irrespective of the factor of production we analyze. In these sectors, we have no evidence of economic interdependencies between neighboring regions. The visible spatial error autocorrelation is simply a sign of potential data problems or regional definitions that do not adequately capture the specific spatial dimension of sectoral specialization patterns. This means that we clearly can reject the assumption of spatial lag dependence of regional specialization in most manufacturing, scale-intensive sectors.

However, there are some exceptions to the prevalence and clearness of the spatial error autocorrelation with respect to some, but not all, labor-intensive sectors. It is thus possible that labor-intensive production or provision of services is positively influenced by the degree of specialization of surrounding regions in some cases.

With respect to investment specialization, these exceptions include the mineral products, various industries, recovery, repair, trade, lodging, and catering services sectors when using the inverse squared distance matrix. The regional investment specialization in one of these three sectors is significantly and positively influenced by that of neighboring regions. According to the spatial association analysis of Section 3, the geographic allocation of regions specialized in these sectors shows that the highest specialization in minerals and mineral products for regions in the central parts of Italy and in recovery, repair, trade, lodging, and catering services for the traditional tourist and coastal Italian regions and the island of Corsica. However, the results of a possible spatial lag dependence need not necessarily be due to economic interactions, but might follow from natural conditions like raw material resources or a shared coastline. No clear geographical location patterns are obvious for those regions particularly specialized in various industries (whose spatial lag parameter was only weakly significant, even according to the inverse squared distance matrix).

In addition, the agriculture, building and construction, other services, and once again, various industries sectors seem, according to the inverse distance matrix, to be subject to significant positive spatial interactions of employment specialization. The spatial patterns of employment specialization reveal that the southern Italian regions as well as the western French regions display the highest levels of specialization in agriculture and in building and construction. However, for various other regions – such as many Belgian regions, Luxembourg, and some regions in northern France – a high specialization in other market services is evident. With respect to various industries, geographic patterns are again less clear; but a high employment specialization is, as for investment specialization, to be found in central and eastern France as well as some northern Italian regions.

We thus do not find strong similar regional clustering patterns for those sectors subject to potential spatial lag dependence. First, clusters vary from sector to sector, with one exception. Second, regional clusters of strongly specialized regions potentially exerting spill-overs to neighboring regions are definitely neither located all in the periphery nor all in the core.

6. REGIONAL DEVELOPMENTS IN THE LIGHT OF SECTORAL SPECIALIZATION AND SPATIAL IMPACTS

To summarize, the Exploratory Spatial Data Analysis (ESDA) using the Getis-Ord statistics does not identify strong clusters of sectoral specialization across those 56 European regions included in the study. There are a very few general clusters of similarly strong specialization in investment and employment (e.g., specialization in agriculture and in building and construction in southern Italy), but these are not very striking. However, we note that according to the local spatial association analysis, identified clusters of either regional employment or investment specialization of the same sector are in most cases located at different places across space. It thus stands to reason that the regional specialization in labor and capital-intensive production of one sector follows different locational patterns.

We only rarely detect significant spatial interdependencies between the level of sectoral specialization of neighboring regions in the econometric analysis, and importantly the identification of the interdependencies is sensitive to the choice of the spatial weights matrix. With respect to the manufacturing sectors, we can clearly reject the assumption of potential spatial lag dependence of regional sectoral specialization due to spillovers or economic interactions.

We also do not find strong or clear negative impacts of economic spillovers or regional interactions of detrimental specialization patterns. First, the spatial clustering of similar sectoral specialization in some rather disadvantaged sectors in the peripheral regions identified in the ESDA analyses is not generally accompanied by significant spatial interdependencies. Agriculture as well as building and construction are the only sectors that are, at least according to the inverse squared distance matrix, marked by significant spatial interdependencies in employment (but not investment) specialization while showing an obvious cluster in some peripheral regions. Second, other sectors possibly subject to spatial interactions are clustered in various geographic locations but not predominantly in the periphery.

However, we have to take note that those few sectors that according to the spatial econometric estimates are potentially exposed to significant spatial interdependencies in regional specialization patterns – agriculture, mineral products, various industries, building and construction, and the services sectors recovery, repair, trade, lodging, catering services, and other services – are quite labor-intensive and cannot be classified as strongly growth-oriented sectors.

In addition, according to the econometric analyses, peripheral regions are significantly more heavily specialized in most services sectors as well as building and construction. Therefore, though we do not identify strong clusters of regional specialization in the local spatial association analyses, peripheral regions might be predominantly affected by the positive spatial interdependencies in employment specialization identified for the building industry and other services as well as in investment specialization identified for recovery, repair, trade, lodging, and catering services. Depending on the nature of these activities, the spatial dependence of specialization might exhibit a disadvantageous and low growth outlook for those regions very far located from the core regions.

Thus, peripheral regions' specialization in building and construction reflects infrastructural activities that are probably regional policy activities and not private sector activities. The quality of the specialization in other services and recovery, repair, trade, lodging, and catering services, however, would have to be assessed on the basis of more precise information, i.e., more highly disaggregated data. Trade and lodging can be assumed to be driven mainly by small enterprises, a result of these peripheral regions' tendency to be located along coasts. Other services contain a rather broad spectrum of economic activities that makes evaluation difficult. These include tourism-related services (such as renting) but also business services (such as advertising and consulting).

We might thus be confronted with some disadvantageous spatial interdependencies in the periphery. These are, however, not very strong and not consistently detectable by the use of different spatial weights matrices. In addition, there is no evidence of favorable spatial interdependencies in the center and thus no obvious evidence of a further self-increase in core-periphery tendencies.

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APPENDIX

TABLE A1

Abbreviation of NUTS 2 Regions

France		Italia		Belgique	
Alsace	ALS	Abruzzo	ABR	Antwerpen	ANT
Aquitaine	AQU	Basilicata	BAS	Brabant Wallon	BWA
Auvergne	AUV	Calabria	CAL	Bruxelles-Capitale	BRU
Basse-Normandie	BNO	Campania	CAM	Hainaut	HAI
Bourgogne	BOU	Emilia-Romagna	ERO	Liège	LIE
Bretagne	BRT	Friuli-Venezia Giulia	FVG	Limburg (B)	LIM
Centre (F)	CTR			Luxembourg (B)	LUB
Champagne-Ardenne	CHA	Lazio	LAZ	Namur	NAM
Corse	CRS	Liguria	LIG	Oost-Vlaanderen	OVL
Franche-Comté	FRC	Lombardia	LOM	Vlaams Brabant	VBR
Haute-Normandie	HNO	Marche	MAR	West-Vlaanderen	WVL
Île de France	IDF	Molise	MOL		
Languedoc-Roussillon	LRO	Piemonte	PIE		
Limousin	LIS	Puglia	PUG		
Lorraine	LOR	Sardegna	SAR		
Midi-Pyrénées	MPY	Sicilia	SIC		
Nord - Pas-de-Calais	NPC	Toscana	TOS		
Pays de la Loire	PDL	Trentino-Alto Adige	TAA	Monoregional Countries	
Picardie	PIC				
Poitou-Charentes	POI	Umbria	UMB	Danmark	DEN
Provence-Alpes-Côte d'Azur	PAC	Valle d'Aosta	VAO	Ireland	IRE
		Veneto	VEN	Luxembourg	LUX
Rhône-Alpes	RAL				

TABLE A2

Abbreviation and Data Sources of Variables

Abbreviation	Variable	Unit
Data Source: Eurostat REGIO Database; yearbooks up to 2000, ESA 79		
GFCF	Gross Fixed Capital Formation	Currency: billions of ECU
EMP	Total Employment	in 1000 persons
PODEN	Population Density	in 1000 inhabitants/km2
GRP	Gross Regional Product	Currency: billions of ECU
AREA	Regional Size	km²
UEWP	Total Unemployment Rates	in % of working population
Data Source: own construction		
DIST	Distance to Centre, index of peripherality	1000 km
CENTR	Regional dummy set for central region	0 or 1
Country dummies		
Data Source: Quinn (1997)		
QUINN_OPENN	Indicator of Openness per country	0-14 (variation by 0.5)

TABLE A3

Descriptive Statistics

Variable	Number of Observations	Mean	Std. Dev.	Min	Max
CENTR	560	0.1	0.3	0.0	1.0
PODEN	560	283.1	783.1	28.3	6062.0
DIST	560	337.2	281.3	1.0	1350.7
GRP	560	35061.6	41829.5	1441.0	329603.0
QUINNN_OPENN	560	12.1	1.4	10.0	14.0
AREA	560	17709.9	14035.7	161.4	70273.1
UEWP	560	9.9	4.1	1.5	23.2
SP.GFCF.EU $_j$					
AGRO	377	2.1	1.1	0.0	5.6
FUEL	387	2.0	2.8	0.3	23.9
META	355	1.1	2.2	0.0	19.8
MINE	371	1.1	0.7	0.0	4.2
CHEM	370	0.5	0.4	0.0	3.1
METP	371	0.5	0.3	0.0	1.3
TREQ	358	0.8	1.0	0.0	10.0
FOOD	371	0.8	0.5	0.1	3.6
TEXT	364	0.7	0.7	0.0	3.8
PAPE	371	0.7	0.7	0.0	6.5
VARI	371	1.1	0.7	0.1	4.7
BUIL	387	0.4	0.1	0.2	1.1
TRLO	358	0.6	0.2	0.1	1.7
TRCO	363	1.4	0.6	0.4	4.0
CRED	363	0.4	0.3	0.1	3.3
OTHS	358	2.0	0.4	1.2	3.3
NMSE	377	0.8	0.4	0.2	2.1
SP.EMP.EU $_j$					
AGRO	494	3.0	1.9	0.0	9.9
FUEL	425	0.3	0.2	0.1	1.9
META	413	0.7	0.9	0.0	6.1
MINE	418	1.1	0.6	0.1	3.3
CHEM	413	0.4	0.2	0.1	1.6
METP	416	0.7	0.4	0.1	1.6
TREQ	417	0.6	0.6	0.0	3.7
FOOD	418	0.8	0.3	0.2	1.9
TEXT	418	1.7	1.7	0.0	8.2
PAPE	418	0.5	0.3	0.0	1.4
VARI	416	1.7	0.9	0.3	5.2
BUIL	425	1.2	0.3	0.6	2.5
TRLO	416	1.3	0.2	0.9	2.0
TRCO	416	0.9	0.2	0.4	1.7
CRED	416	0.4	0.3	0.1	2.1
OTHS	418	0.8	0.2	0.3	1.3
NMSE	425	1.3	0.3	0.8	2.3

TABLE A4

Spatial Econometric Analysis (Spatial Lag and Spatial Error Model) of Investment Specialization Patterns

OLS/Spatial Lag/Error	AGRO			FUEL		
	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		0.428***			-0.503**	
CONSTANT	3.664***	2.958***	4.514***	-0.387	0.204	-0.868**
CENTR	-0.715***	-0.851***	-0.725***	0.609***	0.779***	1.417***
PODEN	-6.882***	-7.526***	-7.366***	-1.328*	-1.323*	-0.372
DIST	-1.071***	-1.101***	-0.537***	0.174	0.260	0.447***
GRP	0.012***	0.015***	0.015***	0.001	0.001	0.001
QUINN_OPEN	-0.014	-0.024	-0.030	0.096***	0.099***	0.096***
AREA	-0.021***	-0.024***	-0.021***	0.012**	0.011*	0.015***
UEWP	0.066***	0.053***	0.011	0.097***	0.117***	0.105***
DUM_FRA	-1.331***	-0.975***	-1.294***	-0.734***	-0.926***	-0.695***
DUM_IRE	0.876**	1.455***	1.370***	-2.367***	-2.736***	-3.076***
DUM_DEN	-1.049***	-0.804**	-1.039***	-0.636*	-0.831**	-1.222***
DUM_LUX	-1.135***	-0.633*	-0.854**	-0.717**	-0.853**	-0.615**
LAMBDA			0.929***			-1.749***
Breusch-Pagan test		62.55***	53.01***		53.63***	77.74***
LR-test		12.44***	17.63***		6.41**	53.25***
LM-Error/Lag test		14.46***	25.09***		19.65***	2.43
AIC	2.118	2.090	2.071	2.176	2.165	2.035
No. of Obs.	377			377		

OLS/Spatial Lag/Error	META			MINE		
	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		-1.369***			0.678***	
CONSTANT	3.532***	5.644***	5.582***	1.903***	0.937**	1.641***
CENTR	-1.372*	-1.809***	-2.130***	-0.851***	-1.032***	-1.003***
PODEN	-4.319**	-4.477**	-11.191***	-1.355**	-1.525***	-1.344***
DIST	-0.740	-1.121**	-0.939**	-0.720***	-0.742***	-0.649***
GRP	0.014*	0.016**	0.039***	0.004*	0.005**	0.004**
QUINN_OPEN	-0.070	-0.086	-0.167**	0.003	0.000	0.002
AREA	-0.059***	-0.074***	-0.126***	0.000	-0.001	-0.004
UEWP	-0.012	-0.029	0.031	-0.010	-0.001	-0.002
DUM_FRA	0.470	0.955***	0.828***	-0.740***	-0.393***	-0.469***
DUM_IRE	2.985*	5.138***	7.185***	0.148	0.625	0.708
DUM_DEN	—			—		
DUM_LUX	3.321***	3.996***	3.512***	0.166	0.764**	0.628*
LAMBDA			-1.875***			0.799***
Breusch-Pagan test		363.81***	341.16***		106.76***	115.55***
LR-test		37.33***	72.31***		22.34***	18.12***
LM-Error/Lag test		0.83	29.16***		24.11***	6.55**
AIC	4.351	4.251	4.147	1.790	1.734	1.740
No. of Obs.	353			361		

TABLE A4 (Continued)

OLS/Spatial Lag/Error	CHEM OLS	CHEM Lag	CHEM Error	METP OLS	METP Lag	METP Error
W_SPCFEU		0.110			-0.462***	
CONSTANT	0.398*	0.334	0.352	0.876***	1.214***	0.962***
CENTR	-0.551***	-0.544***	-0.479***	-0.705***	-0.694***	-0.605***
PODEN	-0.430	-0.450	-0.554	-0.010	0.094	0.132
DIST	-0.329***	-0.331***	-0.388***	-0.377***	-0.358***	-0.267***
GRP	0.005***	0.004***	0.004***	0.003***	0.003***	0.002***
QUINN_OPEN	0.009	0.009	0.012	0.000	0.000	0.002
AREA	-0.002	-0.002	0.000	0.003*	0.003*	-0.001
UEWP	0.010**	0.011**	0.016***	-0.035***	-0.045***	-0.043***
DUM_FRA	-0.017	-0.026	-0.081	-0.013	0.011	0.044***
DUM_IRE	0.892***	0.847***	0.592**	0.760***	0.875***	1.021***
DUM_DEN	—			—		
DUM_LUX	0.237	0.233	0.145	0.230*	0.168	0.103
LAMBDA			0.434*			-1.779***
Breusch-Pagan test		109.36***	115.66***		35.20***	19.58**
LR-test		0.33	0.79		12.82***	84.35***
LM-Error/Lag test		1.99	36.11***		26.14***	72.02***
AIC	0.824	0.828	0.822	-0.204	-0.234	-0.438
No. of Obs.	360			361		

OLS/Spatial Lag/Error	TREQ OLS	TREQ Lag	TREQ Error	FOOD OLS	FOOD Lag	FOOD Error
W_SPCFEU		-0.032			-0.261	
CONSTANT	0.356	0.376	0.365	0.849***	1.063***	0.915***
CENTR	-0.567*	-0.567*	-0.565*	-0.872***	-0.883***	-1.164***
PODEN	-0.982	-0.960	-1.011	-1.006***	-0.899**	-0.724*
DIST	-0.840***	-0.849***	-0.838***	-0.897***	-0.948***	-1.033***
GRP	0.004	0.004	0.004	0.003**	0.003**	0.002*
QUINN_OPEN	0.081*	0.081*	0.081*	0.039**	0.039**	0.039***
AREA	-0.015*	-0.015*	-0.015*	-0.003	-0.003	-0.003
UEWP	0.004	0.004	0.003	-0.012**	-0.014***	-0.016***
DUM_FRA	0.188	0.188	0.187	0.288***	0.341***	0.289***
DUM_IRE	0.425	0.419	0.432	2.055***	2.132***	2.378***
DUM_DEN	—			—		
DUM_LUX	-0.484	-0.474	-0.499	0.216	0.238	0.227
LAMBDA			0.024			-1.162***
Breusch-Pagan test		112.08***	111.13***		78.75***	76.59***
LR-test		0.02	0.01		2.99*	35.25***
LM-Error/Lag test		1.40	1.40		40.15***	151.14***
AIC	2.814	2.820	2.814	0.814	0.811	0.716
No. of Obs.	353			361		

TABLE A4 (Continued)

OLS/Spatial	TEXT			PAPE		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		-0.388*			-0.180	
CONSTANT	1.550***	2.022***	1.778***	1.291***	1.448***	1.334***
CENTR	-1.786***	-1.702***	-1.451***	-0.465**	-0.435**	-0.174
PODEN	-0.959*	-0.771	-0.597	0.083	0.117	0.227
DIST	-0.695***	-0.608***	-0.644***	-0.621***	-0.646***	-0.598***
GRP	0.011***	0.010***	0.007***	0.001	0.001	0.000
QUINN_OPEN	-0.021	-0.018	-0.010	-0.005	-0.005	-0.001
AREA	0.003	0.002	0.000	-0.002	-0.002	-0.002
UEWP	-0.015*	-0.028***	-0.041***	-0.038***	-0.042***	-0.049***
DUM_FRA	-0.797***	-0.951***	-0.804***	0.177***	0.202***	0.191***
DUM_IRE	0.753*	0.730*	0.804**	0.647	0.663	0.459
DUM_DEN	—			—		
DUM_LUX	1.950***	1.617***	1.676***	-0.397	-0.410	-0.580**
LAMBDA			-1.437***			-0.821**
Breusch-Pagan test		96.11***	133.82***		226.94***	218.75***
LR-test		6.29**	33.86***		0.74	7.48***
LM-Error/Lag test		0.18	111.97***		4.89**	46.64***
AIC	1.697	1.685	1.603	1.651	1.654	1.630
No. of Obs.	360			361		

OLS/Spatial	VARI			BUIL		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		0.363*			0.553***	
CONSTANT	1.889***	1.366***	1.869***	0.730***	0.528***	0.779***
CENTR	-1.211***	-1.222***	-1.207***	0.087**	0.102***	0.140***
PODEN	-0.355	-0.546	-0.371	-0.418***	-0.459***	-0.456***
DIST	-0.664***	-0.689***	-0.666***	0.054**	0.038	0.040
GRP	0.002	0.003	0.002	0.001**	0.001***	0.001***
QUINN_OPEN	0.007	0.006	0.007	-0.028***	-0.028***	-0.028***
AREA	0.009*	0.009	0.009*	-0.001	-0.001	-0.001
UEWP	-0.066***	-0.051***	-0.063***	0.010***	0.007***	0.005**
DUM_FRA	-0.114	-0.154*	-0.118	-0.066***	-0.042***	-0.015
DUM_IRE	0.552	0.451	0.536	-0.244***	-0.210***	-0.219***
DUM_DEN	—			-0.065	-0.067	-0.090*
DUM_LUX	1.640***	1.740***	1.668***	-0.412***	-0.152***	-0.163***
LAMBDA			0.115			0.889***
Breusch-Pagan test		57.98***	57.04***		77.35***	75.88***
LR-test		4.30**	0.18		9.73***	10.22***
LM-Error/Lag test		19.34***	6.07**		18.54***	18.59***
AIC	1.973	1.967	1.973	-1.674	-1.695	-1.701
No. of Obs.	361			377		

TABLE A4 (Continued)

OLS/Spatial	TRLO			TRCO		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		0.866^{***}			-0.449^{**}	
CONSTANT	0.754^{***}	0.156	0.644^{***}	-0.015	0.830^{*}	0.681^{***}
CENTR	0.135^{**}	0.205^{***}	0.239^{***}	1.612^{***}	1.529^{***}	1.556^{***}
PODEN	0.535^{***}	0.556^{***}	0.512^{***}	2.698^{***}	2.299^{***}	0.464
DIST	0.210^{***}	0.163^{***}	0.160^{***}	0.461^{***}	0.513^{***}	0.698^{***}
GRP	-0.002^{***}	-0.002^{***}	-0.002^{***}	-0.011^{***}	-0.010^{***}	-0.001
QUINN_OPEN	-0.011	-0.008	-0.007	0.106^{***}	0.099^{***}	0.068^{***}
AREA	0.005^{***}	0.005^{***}	0.005^{***}	0.016^{***}	0.013^{***}	-0.003
UEWP	-0.025^{***}	-0.014^{***}	-0.011^{***}	-0.026^{***}	-0.029^{***}	-0.029^{***}
DUM_FRA	-0.049^{**}	-0.035	-0.029	-0.341^{***}	-0.453^{***}	-0.275^{***}
DUM_IRE	—			-1.249^{***}	-1.131^{***}	-0.300
DUM_DEN	—			—		
DUM_LUX	-0.111	-0.057	-0.040	-1.623^{***}	-1.711^{***}	-1.555^{***}
LAMBDA			0.954^{***}			-1.934^{***}
Breusch-Pagan test		179.82^{***}	186.18^{***}		91.89^{***}	143.35^{***}
LR-test		36.34^{***}	33.29^{***}		5.57^{**}	42.41^{***}
LM-Error/Lag test		22.56^{***}	1.46		3.03^{*}	34.71^{***}
AIC	-0.430	-0.526	-0.523	1.219	1.209	1.102
No. of Obs.	358			363		

OLS/Spatial	CRED			OTHS		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		-0.097^{***}			0.691^{***}	
CONSTANT	0.352^{***}	0.392^{***}	0.338^{***}	2.642^{***}	1.381^{***}	3.368^{***}
CENTR	0.086^{***}	0.077^{**}	0.086^{***}	0.270^{***}	0.214^{**}	0.035
PODEN	0.476^{***}	0.473^{***}	0.447^{***}	1.392^{***}	1.583^{***}	1.404^{***}
DIST	0.016	0.009	-0.002	0.257^{***}	0.332^{***}	0.400^{***}
GRP	-0.001^{**}	-0.001^{**}	-0.001^{**}	-0.002^{**}	-0.002^{**}	-0.001
QUINN_OPEN	-0.008^{*}	-0.008^{*}	-0.009^{**}	-0.098^{***}	-0.100^{***}	-0.107^{***}
AREA	0.004^{***}	0.004^{***}	0.003^{***}	0.001	0.000	0.000
UEWP	-0.010^{***}	-0.011^{***}	-0.008^{***}	0.020^{***}	0.008^{**}	-0.006
DUM_FRA	0.075^{***}	0.090^{***}	0.104^{***}	0.153^{***}	0.128^{***}	0.250^{***}
DUM_IRE	0.480^{***}	0.501^{***}	0.528^{***}	—		
DUM_DEN	—			—		
DUM_LUX	2.448^{***}	2.449^{***}	2.547^{***}	-0.841^{***}	-0.957^{***}	-0.776^{***}
LAMBDA			0.836^{***}			0.979^{***}
Breusch-Pagan test		214.02^{***}	263.41^{***}		32.09^{***}	28.76^{***}
LR-test		7.02^{***}	12.58^{***}		15.71^{***}	63.83^{***}
LM-Error/Lag test		8.28^{***}	2.60		35.49^{***}	1.57
AIC	1.771	-1.785	-1.806	0.165	0.127	-0.013
No. of Obs.	363			358		

TABLE A4 (Continued)

OLS/Spatial Lag/Error	OLS	NMSE Lag	Error
W_SPCFEU		-0.254	
CONSTANT	0.481***	0.628***	0.470***
CENTR	0.120	0.102	-0.005
PODEN	-0.528***	-0.533**	-1.019***
DIST	0.473***	0.480***	0.462***
GRP	-0.001	-0.001	0.001
QUINN_OPEN	0.010	0.010	0.005
AREA	-0.008***	-0.007***	-0.006***
UEWP	0.008***	0.009***	0.015***
DUM_FRA	0.503***	0.568***	0.486***
DUM_IRE	0.199	0.212	0.086
DUM_DEN	0.473***	0.497***	0.384***
DUM_LUX	0.575***	0.681***	0.570***
LAMBDA			-1.454***
Breusch-Pagan test		136.53***	113.24***
LR-test		3.50*	47.61***
LM-Error/Lag test		15.24***	138.98***
AIC	0.018	0.014	-0.108
No. of Obs.	377		

***/**/* refers to a significance level of 1/5/10 percent.

TABLE A5

Spatial Econometric Analysis (Spatial Lag and Spatial Error Model) of Employment Specialization Patterns

OLS/Spatial Lag/Error	AGRO			FUEL		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		0.896***			-0.307	
CONSTANT	1.744***	0.105	16.404***	0.098	0.165*	0.093
CENTR	-0.103	-0.955***	-0.766***	0.053	0.050	0.118**
PODEN	-0.252***	-0.087	-0.044	-0.036**	-0.039***	-0.102***
DIST	0.000**	-0.642***	-0.298	0.000***	0.135***	0.198***
GRP	-0.017***	-0.014***	-0.013***	0.000	0.000	0.001***
QUINN_OPEN	0.113***	0.066**	0.057*	0.003	0.003	0.000
AREA	0.012*	0.001	-0.001	-0.003**	-0.003**	-0.002*
UEWP	0.165***	0.068***	0.053***	0.009***	0.009***	0.006***
DUM_FRA	-1.385***	-0.225*	-0.777***	0.123***	0.139***	0.111***
DUM_IRE	-0.869	2.318***	2.063***	0.243**	0.258**	0.187*
DUM_DEN	-1.274**	0.766*	0.425	0.019	0.035	-0.058
DUM_LUX	-2.091***	-0.988**	-1.322***	-0.004	0.018	-0.109
DUM_BEL	-2.950***	-0.895***	-0.949**	0.128***	0.153***	0.239***
LAMBDA			0.988***			-1.269***
Breusch-Pagan test		181.598***	232.323***		455.550***	396.535***
LR-test		146.902***	155.176***		2.744*	19.711***
LM-Error/Lag test		188.392***	0.029		0.555	63.488***
AIC	3.007	2.713	2.774	-0.628	-0.629	-0.674
No. of Obs.	494			425		

OLS/Spatial Lag/Error	Meta			Mine		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		-0.234***			-0.304	
CONSTANT	1.050***	1.232***	1.164***	1.321***	1.740***	1.531***
CENTR	-0.575***	-0.553***	-0.432**	-0.450**	-0.400**	-0.304*
PODEN	-0.090*	-0.100*	-0.163***	-0.104**	-0.120***	-0.317***
DIST	0.000	0.318*	0.692***	0.000***	-0.502***	-0.572***
GRP	0.002	0.002*	0.003***	-0.002**	-0.002**	-0.002**
QUINN_OPEN	-0.012	-0.014	-0.021	0.032*	0.031*	0.024
AREA	-0.019***	-0.021***	-0.029***	0.001	0.002	0.010***
UEWP	-0.016**	-0.020***	-0.028***	-0.011*	-0.014**	-0.029***
DUM_FRA	0.194**	0.271***	0.277***	-0.406***	-0.494***	-0.531***
DUM_IRE	1.396***	1.582***	2.024***	0.251	0.084	-0.390
DUM_DEN	0.548*	0.672**	0.776***	-0.324	-0.465*	-0.820***
DUM_LUX	4.839***	4.791***	3.985***	0.292	0.048	-0.636**
DUM_BEL	0.393***	0.581***	0.654***	-0.431***	-0.531***	-0.215***
LAMBDA			-1.414***			-1.376***
Breusch-Pagan test		104.595***	84.380***		125.747***	85.120***
LR-test		10.825***	81.105***		3.699*	28.943***
LM-Error/Lag test		35.364***	197.123***		0.112	83.495***
AIC	1.889	1.868	1.693	1.599	1.595	1.530
No. of Obs.	413			418		

TABLE A5 (Continued)

OLS/Spatial Lag/Error	CHEM			METP		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		0.098			0.126	
CONSTANT	0.279***	0.240*	0.248***	1.062***	0.941***	1.215***
CENTR	-0.250***	-0.245***	-0.158**	-0.850***	-0.848***	-0.891***
PODEN	-0.010	-0.014	0.056***	0.103***	0.101***	0.057***
DIST	0.000***	-0.917***	-0.029	0.000***	-0.434***	-0.298***
GRP	0.003***	0.003***	0.003***	0.006***	0.006***	0.006***
QUINN_OPEN	0.004	0.004	0.001	-0.019**	-0.017**	-0.024***
AREA	-0.001	-0.001	-0.003**	0.003**	0.004**	-0.002
UEWP	0.000	0.000	-0.002	-0.028***	-0.025***	-0.037***
DUM_FRA	0.070**	0.061*	0.113***	0.185***	0.170***	0.240***
DUM_IRE	0.289*	0.258*	0.440***	0.763***	0.718***	1.175***
DUM_DEN	0.048	0.028	0.085	0.517***	0.503***	0.720***
DUM_LUX	0.061	0.063	-0.223**	0.602***	0.653***	0.222*
DUM_BEL	0.199***	0.185***	0.230***	-0.054	-0.048	-0.017
LAMBDA			-1.496***			-1.263***
Breusch-Pagan test		209.551***	109.960***		59.594***	83.716***
LR-test		0.366	51.509***		1.373	26.925***
LM-Error/Lag test		32.220***	40.388***		47.915***	88.465***
AIC	-0.213	-0.209	-0.338	0.011	0.012	-0.054
No. of Obs.	413			416		

OLS/Spatial Lag/Error	TREQ			FOOD		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		-0.516***			-0.208	
CONSTANT	0.858***	1.223***	0.966***	0.918***	1.070***	0.956***
CENTR	-0.599***	-0.635***	-0.670***	-0.532***	-0.539***	-0.645***
PODEN	0.072	0.072*	-0.001	0.011	0.014	0.005
DIST	0.000***	-0.433***	-0.210**	0.000***	-0.513***	-0.563***
GRP	0.004***	0.004	0.004***	0.000	0.000	0.000
QUINN_OPEN	-0.010	-0.012	-0.013	0.001	0.001	0.001
AREA	-0.009**	-0.011***	-0.019***	0.002	0.002	0.001
UEWP	-0.005	-0.008	-0.008*	-0.017***	-0.017***	-0.016***
DUM_FRA	0.574***	0.715***	0.702***	0.442***	0.495***	0.436***
DUM_IRE	0.650*	0.910***	1.383***	1.082***	1.136***	1.206***
DUM_DEN	0.346	0.485*	0.742***	0.813***	0.846***	0.915***
DUM_LUX	-0.056	-0.151	-0.576**	0.315***	0.339***	0.211**
DUM_BEL	-0.019	0.016	0.032	0.156***	0.193***	0.137***
LAMBDA			-1.199***			-0.952***
Breusch-Pagan test		73.754***	84.388***		78.341***	90.496***
LR-test		15.034***	50.929***		3.232*	32.050***
LM-Error/Lag test		0.017	163.045***		24.752***	114.541***
AIC	1.519	1.488	1.397	-0.250	-0.253	-0.327
No. of Obs.	417			418		

TABLE A5 (Continued)

OLS/Spatial	TEXT			PAPE		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		0.792***			0.289**	
CONSTANT	3.987***	1.147*	3.662**	0.878***	0.669***	0.658***
CENTR	-3.978***	-4.462***	-4.456***	-0.183***	-0.186***	-0.228***
PODEN	0.534***	0.622***	0.701***	0.044***	0.000**	0.001
DIST	-0.003***	-2.649***	-2.340***	0.000***	-0.399***	-0.407***
GRP	0.013***	0.016***	0.018***	0.003***	0.000***	0.004***
QUINN_OPEN	0.010	0.025	4.681	-0.015**	-0.014**	-0.013**
AREA	0.020**	0.025***	0.022***	0.001	0.000	0.002
UEWP	-0.119***	-0.068***	-0.100***	-0.024***	-0.020***	-0.017***
DUM_FRA	-1.385***	-0.560***	0.040	0.220***	0.171***	0.143***
DUM_IRE	1.201	1.966**	2.927***	0.419***	0.340***	0.264**
DUM_DEN	-0.612	0.420	0.863	0.295***	0.255***	0.095**
DUM_LUX	0.147	2.784***	3.348***	0.018	0.059	0.059
DUM_BEL	-2.021***	-0.682***	-0.001	0.156***	0.091**	-0.095
LAMBDA			0.952***			0.839***
Breusch-Pagan test		157.846***	146.692***		134.212***	129.379***
LR-test		52.460***	67.145***		6.340**	23.271***
LM-Error/Lag test		55.413***	24.655***		5.673**	51.590***
AIC	3.331	3.210	3.170	-0.512	-0.522	-0.567
No. of Obs.	418			418		

OLS/Spatial	VARI			BUIL		
Lag/Error	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		0.791***			0.453***	
CONSTANT	3.061***	1.164***	2.894***	0.581***	0.185	0.403***
CENTR	-0.325***	-1.351***	-1.206***	0.132*	0.098	0.104
PODEN	0.046	0.052	0.084	-0.128***	-0.117***	-0.120***
DIST	-0.001***	-0.763***	-0.650***	0.001***	0.467***	0.467***
GRP	0.002	0.003**	0.003**	-0.001***	-0.001***	-0.001**
QUINN_OPEN	-0.031	-0.015	-0.022	0.020***	0.016**	0.026***
AREA	0.019***	0.018***	0.021***	-0.007***	-0.007***	-0.007***
UEWP	-0.100***	-0.062***	-0.074***	0.039***	0.029***	0.053***
DUM_FRA	-0.136	-0.131	-0.008	0.032	0.058*	0.043*
DUM_IRE	0.278	0.091	0.080	0.068	0.209	0.039
DUM_DEN	0.140	0.190	0.088	0.239**	0.284***	0.271***
DUM_LUX	0.691	1.075***	1.060**	0.631***	0.574***	0.810***
DUM_BEL	-0.347**	-0.007	0.154	0.042	0.074*	0.021
LAMBDA			0.865***			-1.106***
Breusch-Pagan test		84.112***	78.926***		127.623***	89.657***
LR-test		39.543***	30.240***		22.883***	10.491***
LM-Error/Lag test		25.302***	0.151		120.852***	201.569***
AIC	2.344	2.254	2.272	-0.148	-0.198	-0.173
No. of Obs.	416			425		

TABLE A5 (Continued)

OLS/Spatial Lag/Error	TRLO			TRCO		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		-0.950***			-0.488**	
CONSTANT	1.662***	3.002***	1.605***	0.844***	1.313***	0.871***
CENTR	0.066	0.042	0.108**	0.347***	0.319***	0.397***
PODEN	-0.005	0.016	0.004***	-0.036**	0.000**	0.000*
DIST	0.000***	0.394***	0.327***	0.000***	0.211***	0.263***
GRP	-0.001**	0.000	0.000	0.001***	0.000***	0.000***
QUINN_OPEN	-0.015***	-0.017***	-0.016***	0.004	0.002	-0.001
AREA	-0.002**	-0.002**	0.000	-0.005***	0.000***	0.000***
UEWP	-0.011***	-0.015***	-0.012***	-0.007***	-0.010***	-0.012***
DUM_FRA	-0.295***	-0.454***	-0.308***	0.027	0.017	0.023
DUM_IRE	0.055	-0.031	-0.083	-0.078	-0.043	-0.100
DUM_DEN	-0.357***	-0.436***	-0.478***	-0.059	-0.054	-0.157**
DUM_LUX	-0.113	-0.286***	-0.301***	-0.230**	-0.229**	-0.221***
DUM_BEL	-0.125***	-0.176***	-0.072***	0.008	0.000	0.040*
LAMBDA			-1.589***			-1.574***
Breusch-Pagan test		60.624***	72.810***		95.820***	79.322***
LR-test		50.352***	138.853***		9.059***	94.779***
LM-Error/Lag test		2.260	16.379***		34.273***	69.720***
AIC	-0.904	-1.020	-1.238	-0.545	-0.562	-0.772
No. of Obs.	416			416		

OLS/Spatial Lag/Error	CRED			OTHS		
	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		-0.136***			0.312***	
CONSTANT	0.219***	0.280***	0.242***	0.667***	0.436***	0.648***
CENTR	0.234***	0.224***	0.213***	0.303***	0.330***	0.335***
PODEN	0.250***	0.245***	0.243***	0.000	-0.006	0.003
DIST	0.000	0.015	0.017	0.000***	0.156***	0.174***
GRP	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
QUINN_OPEN	0.000	0.000	-0.001	-0.009***	-0.008***	-0.009***
AREA	0.002***	0.001***	0.003***	0.000	0.000	0.001
UEWP	-0.006***	-0.007***	-0.008***	-0.003***	-0.002**	-0.003***
DUM_FRA	0.155***	0.177***	0.145***	0.252***	0.191***	0.251***
DUM_IRE	0.148***	0.188***	0.120***	-0.603***	-0.694***	-0.641***
DUM_DEN	0.181***	0.211***	0.164***	-0.370***	-0.442***	-0.397***
DUM_LUX	1.089***	1.091***	1.008***	-0.035	-0.108**	-0.182***
DUM_BEL	0.164***	0.215***	0.182***	0.414***	0.318***	0.442***
LAMBDA			-1.452***			-0.733**
Breusch-Pagan test		63.845***	75.161***		49.522***	79.063***
LR-test		13.641***	61.112***		12.914***	5.300**
LM-Error/Lag test		31.808***	0.836		38.744***	40.698***
AIC	-2.627	-2.655	-2.774	-1.956	-1.982	-1.968
No. of Obs.	416			418		

TABLE A5 (Continued)

OLS/Spatial Lag/Error	OLS	NMSE Lag	Error
W_SPEMEU		-0.698***	
CONSTANT	0.775***	1.592***	0.604***
CENTR	0.781***	0.731***	0.706***
PODEN	-0.085***	-0.077***	-0.061***
DIST	0.000***	0.158***	0.249***
GRP	-0.003***	-0.003***	-0.003***
QUINN_OPEN	0.021***	0.024***	0.022***
AREA	0.000	0.000	-0.001
UEWP	0.020***	0.027***	0.023***
DUM_FRA	0.033	0.077***	0.040
DUM_IRE	-0.414***	-0.353***	-0.272***
DUM_DEN	0.334***	0.432***	0.434***
DUM_LUX	-0.903***	-0.371***	-1.281***
DUM_BEL	0.377***	0.501***	0.403***
LAMBDA			0.945***
Breusch-Pagan test		201.816***	111.626***
LR-test		54.358***	65.563***
LM-Error/Lag test		122.005***	66.555***
AIC	-0.761	-0.884	-0.915
No. of Obs.	425		

***/**/* refers to a significance level of 1/5/10 percent.