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Economic Research

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Non-technical Summary

Economic integration is supposed to foster specialisation. However, specialisation has different facets and might not be favourable for each region. Thus fears of increasing core-periphery tendencies have risen since the seminal study of Krugman (1991) on potential agglomeration tendencies in EMU. Regional specialisation and sectoral location patterns as well as their determinants are thus prominent questions of regional economics during the last years.

This paper investigates the determinants of regional specialisation patterns in 17 different sectors accounting for spatial interaction or autocorrelation. In the analysis, we find significant spatial autocorrelation effects for most sectors – independent of the analysis of investments and employment. However, these do not influence the results on the economic determinants of sectoral specialisation of EU regions of a previous study (Stirboeck, 2004).

Though spatial autocorrelation is present, it is mostly due to spatial error autocorrelation, i.e. for most sectors, we have no evidence of economic interdependencies between neighbouring regions. The spatial error autocorrelation, which is evident, simply is an indication of potential data problems or inadequate regional definitions to capture the specific spatial dimension of sectoral specialisation patterns.

However, there are some exceptions to the prevalence of the spatial error autocorrelation with respect to some, but not all, labour-intensive sectors. Though it seems that labour-intensive production is positively influenced by the degree of specialisation of surrounding regions in some cases. But, the spatial clustering of similar sectoral specialisation in some rather unfavourable sectors in the peripheral regions identified in the exploratory spatial data analyses is not generally accompanied by significant spatial interdependencies. Agriculture and building & construction are the only sectors which are marked by significant spatial interdependencies in employment (but not investment) specialisation while showing an obvious cluster in some peripheral regions. The other four sectors subject to spatial interactions are clustered in different geographic locations, but not predominantly in the periphery. We thus need not fear strong potential negative spill-overs or regional interactions of unfortunate specialisation patterns.

However, we have to take note that those few sectors which are subject to significant spatial interdependencies in regional specialisation patterns are rather labour-intensive and cannot be classified as strongly growth-oriented sectors. These are agriculture, non-metallic minerals & mineral products, various industries, building & construction, and the services sectors trade & lodging and other services. Since peripheral regions are significantly stronger specialised in most services sectors as well as building & construction (while showing very low shares of production in manufacturing), we might be confronted with some disadvantageous spatial interdependencies in the periphery. These, however, do not seem to be very strong. In addition, there is no evidence for favourable spatial interdependencies in the centre and thus no evidence for increasing core-periphery tendencies.

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Abstract
This paper conducts a spatial econometric analysis of the determinants of regional specialisation patterns. Spatial autocorrelation is present, but is mostly due to spatial error autocorrelation. Spatial interaction due to economic interdependencies is only evident for some few labour-intensive sectors. Hereby, sectoral specialisation of a region seems to be positively influenced by the one of surrounding regions. However, we cannot identify clear disadvantageous spatial interdependencies of specialisation in the periphery or increasing core-periphery tendencies.

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I Motivation

Economic integration is supposed to foster specialisation. However, specialisation has different facets and might not be fortunate for each region. Thus fears of increasing core-periphery tendencies have risen since the seminal study of Krugman (1991) on potential agglomeration tendencies in EMU. Regional specialisation and sectoral location patterns as well as the determinants of sectoral location are thus prominent questions of regional economics during the last years.

However, the explanation of the level and the patterns of regional specialisation has been neglected besides the studies by Stirboeck (2002a, 2002b, 2004) as well as Kalemli-Ozcan, Sorensen and Yosha (2003). This article builds on recent research by Stirboeck (2004) which gives insights into the determinants of regional specialisation patterns. According to the traditional and new trade theory, a number of economic determinants are supposed to matter in explaining regional specialisation patterns.

The named study is able to identify locational indicators to be strongly important in explaining regional specialisation patterns. Relative specialisation in manufacturing sectors is higher in central regions. Relative specialisation in services sectors, instead, is stronger in administrative centres as well as peripheral regions. In addition, market potential exerts a significant influence: the specialisation in manufacturing sectors is higher in those regions profiting from higher gross regional product (GRP) levels.

Economic openness (representing market integration) does not play a particular or consistent role in explaining relative specialisation in specific sectors. However, country-specific effects are evident, especially for employment specialisation: hereby Italy differs from the other countries in demonstrating stronger relative employment shares in a number of labour-intensive sectors and weaker ones in manufacturing sectors.

These results demonstrate that peripheral regions – in contrast to core regions – play a different role in attraction sectoral employment and (especially) investments. The driving forces of sectoral specialisation are favourable for core regions with respect to growth-oriented market services. The highest regional specialisation in services sectors in peripheral regions, instead, is linked to economic activity in tourism. In addition to some of the services sectors, relative investments and employment in non-market economic activities are stronger in peripheral regions as well.

However, a shortcoming of these recent analyses is the disregard of space. Analysing regional specialisation tendencies, cross-border spill-overs as well as specialisation clusters might be of strong importance. On the one hand, ignoring regional interdependencies might lead to inefficient inference due to spatial autocorrelation effects. In the extreme case, econometric results on the basis of traditional estimates can be misleading. On the other hand, the existence of regional interactions, i.e. economic interdependencies, are extremely interesting to be directly addressed as well.

Therefore, in this paper, the robustness of the recent findings on the economic and locational determinants of regional specialisation patterns shall be checked controlling for spatial correlation. In addition, spatial interdependencies or interaction driving economic developments or specialisation tendencies are to be analysed.

II Data and Indicators

We analyse EU regions at the NUTS 2-level for the period 1985 to 1994. The definition of NUTS-regions is based on political or administrative criteria, and not on economic criteria. The analysis of NUTS-regions might therefore not give us the actual degree of specialisation of economic entities. However, data on economic or functional regions is not available in official databases. Defining economic regions is arbitrary and depends on the variable or sector regarded, i.e. a general specification of regional disaggregation is inappropriate. The analysis of administrative entities, instead, allows us to focus on the degree of specialisation of a territorial community which is authorised to implement regional policies or is in the focus of regional structural programmes.[1]

Table 1: Sectors disaggregated according to NACE 1970

Sector	Abbr.
Agricultural, forestry and fishery products	AGRO
Manufactured products	
Fuel and power products	FUEL
Ferrous and non-ferrous ores and metals, other than radioactive	META
Non-metallic minerals and mineral products	MINE
Chemical products	CHEM
Metal products, machinery, equipment, electrical goods	METP
Transport equipment	TREQ
Food, beverages, tobacco	FOOD
Textiles and clothing, leather and footwear	TEXT
Paper and printing products	PAPE
Products of various industries	VARI
Building and construction	BUIL
Services	
Recovery, repair, trade, lodging and catering services	TRLO
Transport and communication services	TRCO
Services of credit and insurance institutions	CRED
Other market services	OTHS
Non-market services	NMSE

[1] Since the 1961 Brussels Conference on Regional Economies, regional policies are generally applicated in NUTS 2-regions (Eurostat, 1999).

The maximum number of regions with sufficient sectoral investment and employment data is 56. These regions belong to France (22), Italy (20) and Belgium (11). In addition, the three mono-regional countries Luxembourg, Denmark and Ireland (being also defined as NUTS 2-regions) are included. Due to the fact that the sum of regional investments is not available for the eleven Belgian regions, these are excluded from the empirical analysis of investment specialisation. Up to 17 differentiated sectors (see Table 1) – consistent to Eurostat's industrial classification NACE 1970 (Nomenclature des activités économiques dans les Communautés Européennes) are available in the REGIO database. These refer to agriculture, manufactured products as well as market and non-market services.

Analysing the sectoral specialisation patterns of the 56 regions, we focus on the regional investment and employment shares in relation to an economy of reference. Thus, relative specialisation of gross fixed capital formation in relation to EU patterns (SPCFEU) as well as relative specialisation of employment in relation to EU patterns (SPEMEU) is measured. 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 engagement.[2]

In order to measure relative investment indices, we refer to adapted Balassa-indices[3] which reflect the relative investment performance and the relative employment performance of a region. The sectoral investment (I) share of the respective region s_{ij}^{I} is calculated in relation to the average sectoral share of EU value added $\boldsymbol{r_i}$ [4]:

$$SPCFEU_{ij} = \frac{s_{ij}^{I}}{r_i} = (I_{ij} / \sum_i I_{ij}) / (\sum_j x_{ij} / \sum_i \sum_j x_{ij})$$

with i (j) as the sectoral (regional) index. If the region's investment in one sector is relatively strong (low) compared to the average sectoral share of value added in EU, the index is higher (smaller) than 1.[5]

[2] While measures of absolute allocation are influenced by the sectoral classification, measures of relative allocation are influenced by the sectoral patterns of either the economy of reference or the average pattern of the group of countries included. In case of a very special pattern of the reference economy, the relative specialisation pattern of the economic entities analysed can be biased. See e.g. Stirboeck (2001) or Krieger-Boden (1999).

[3] This kind of specialisation index has first been introduced by Balassa for the analysis of the relative export "performance" of a country by use of export data and is known as the "revealed comparative advantage" index in international trade theory [see e.g. Balassa (1989:19)].

[4] As sectoral GFCF and employment data are not in all cases as complete as we wish it to be, we had to use adequate, but different, data representing the economic extent or importance of the different sectors to calculate sectoral specialisation indices with respect to GFCF. Therefore we refer to data of gross value added at factor costs as the denominator when calculating the specialisation indices in relation to EU average patterns. By this, we apply the same denominator for both specialisation patterns and increase their comparability.

[5] In some few (four) cases, negative investments were replaced by 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.

Relative employment shares have been constructed in a similar way measuring the sectoral employment (L) share of the respective region s_{ij}^{L} in relation to the average sectoral share of EU value added $\boldsymbol{r_i}$:

$$SPEMEU_{ij} = \frac{s_{ij}^{L}}{r_i} = (L_{ij} / \sum_i L_{ij}) / (\sum_j x_{ij} / \sum_i \sum_j x_{ij}) \; .$$

III Spatial Association Patterns: Regional Clusters of Investments and Employment Specialisation

The spatial association patterns can be analysed and described by a number of different statistics. In the following, we refer to a measure of global spatial association, the Moran I statistics, as well as a measure of local spatial association, the Getis-Ord statistics. The latter can be described as a decomposition of the global measure into the contributing factors of spatial association.

Moran's I gives information about 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) in case of a significant clustering of similar (unlike) values. However, it does not differentiate between specific, but different, clusters. The Getis-Ord statistics provides us with further insights. First, it detects clusters of regions with high and low values on the basis of a positive and negative Getis-Ord value respectively. Second, it tells us which regions are significantly marked by positive spatial correlation thus 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 interregional influence on sectoral specialisation should be decreasing with increasing distance. In order to build regional distance matrices, we use the coordinates of the administrative centres of the respective regions since we can assume them to be equivalent to economic centres in most cases.

The Moran I statistics in Table 2 shows significant global spatial association for a number of sectors. In case of significance, the spatial association turns out to be positive, i.e. regions similarly strong or weak in sectoral specialisation are regionally clustered. Any Moran I value being negative turns out to be insignificant. We thus find no evidence for negative spatial autocorrelation induced by a significant systematic spatial allocation of dissimilar values.

With respect to investment specialisation, the significant positive spatial autocorrelation applies to AGRO, FUEL, MINE, METP, FOOD, TEXT, BUIL as well as TRLO and NMSE – with significance at least at the 5%-level, but mostly the 1%-level of significance. Thus, regions with a strong (low) specialisation in one of the named sectors are more likely to be surrounded by regions with an equally strong (low) specialisation than by other regions.

However, there are differences in the spatial association for most sectors with respect to the regional investment specialisation and employment specialisation. Sectors providing evidence of significant (positive) spatial autocorrelation for employment specialisation at the 5%-level of significance are: AGRO, CHEM, FOOD, TEXT, PAPE, VARI, BUIL as well as TRLO and OTHS. Thus, the only sectors which similarly show significant positive spatial clustering for both factors of production are agriculture, food, textiles, building as well as transport & lodging. These are more or less labour-intensive sectors, however, belonging to manufacturing as well as services.

Table 2: Moran I statistics for spatial association

	SPCFEU	SPEMEU
AGRO	0.256 ***	0.500 ***
FUEL	0.191 ***	0.003
META	-0.054	0.036
MINE	0.315 ***	0.045
CHEM	0.016	0.103 **
METP	0.114 **	0.178
TREQ	-0.026	0.043
FOOD	0.117 **	0.268 ***
TEXT	0.129 **	0.253 ***
PAPE	0.085 *	0.278 ***
VARI	0.103 *	0.158 ***
BUIL	0.238 ***	0.258 ***
TRLO	0.225 ***	0.230 ***
TRCO	0.038	-0.013
CRED	-0.022	0.026
OTHS	0.032	0.401 ***
NMSE	0.237 ***	0.038

Note: Significance level is based on calculation of 1000 permutations. ***/**/* refers to a level of 1/5/10 percent significance.

The Getis-Ord statistics provides evidence of local spatial association, i.e. which regions are significantly surrounded by similarly specialised regions. Focusing on the Getis-Ord statistics, we can now differentiate which regions contribute to the global spatial association discussed before and if these regions differ with respect to both, investments and employment.

Table 3: Local spatial association patterns according to Getis-Ord statistics: Agriculture and services sectors

GFCF AGRO	EMP AGRO	GFCF TRLO	EMP TRLO	GFCF TRCO	EMP TRCO	GFCF CRED	EMP CRED	GFCF OTHS	EMP OTHS	GFCF NMSE	EMP NMSE
		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										

Note: Regions are displayed if marked by positive spatial autocorrelation at the 5%-level of significance. GFCF (gross fixed capital formation) represents relative specialisation in investments and EMP the one in employment.

Table 4: Local spatial association patterns according to Getis-Ord statistics: manufacturing sectors

GFCF FUEL	EMP FUEL	GFCF META	EMP META	GFCF MINE	EMP MINE	GFCF CHEM	EMP CHEM	GFCF METP	EMP METP	GFCF TREQ	EMP TREQ	GFCF FOOD	EMP FOOD	GFCF TEXT	EMP TEXT	GFCF PAPE	EMP PAPE	GFCF VARI	EMP VARI	GFCF BUIL	EMP BUIL
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 3.

Employment specialisation mostly shows stronger local spatial association patterns.[6] The only two exceptions are the sectors FUEL as well as MINE. Strong similarity is evident for AGRO, FOOD, TEXT, VARI, PAPE as well as BUIL. This means that the sectors simultaneously showing significant global spatial association according to the Moran I statistics for both, employment and investments, are also marked by similar patterns of local spatial association.[7] This, however, is not the case for TRLO since regional spatial association is different: three (six) Italian regions are marked by spatial autocorrelation of high (low) investment specialisation while seven Italian regions and Corse underlie spatial autocorrelation of high employment specialisation in addition to ten French regions and Ireland showing spatial autocorrelation of low employment specialisation.[8]

For the other sectors, these local spatial association patterns do differ for both factors of production, i.e. those regions marked by local spatial association are not the same. We thus only have evidence for the similarity of the local spatial association of five manufacturing sectors and agriculture.

This means that "hot spots" of spatial association are mostly different. We thus find some clusters of sectoral specialisation across EU regions which are not very striking, but detectable. Southern Italian regions mostly show significant spatial association of high specialisation in agriculture and building, but spatial association of low specialisation for paper & printing industries, metal products etc. as well as the food industries. Some regions of central Italy (TOS, ERO, MAR as well as CRS) form a cluster of high specialisation in mineral industries, other regions of central and northern Italy (ERO, TAA, FVG, UMB, LIG, MAR, TOS and LAZ) as well as CRS in textiles. Most Belgian regions show local spatial autocorrelation of low specialisation in agricultural employment and of high specialisation in credit and other services as well as non-market services and paper & printing products. Besides these clusters, no strong patterns of regional spatial autocorrelation are obvious.

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

[7] Hereby, the Moran I statistics for the paper & printing products industry as well as various industries is only significant at the 10%-level of significance.

[8] The list of regions and their respective abbreviations can be found in the appendix in Table A-1.

IV Sectoral specialisation: Comparing the patterns of investment and employment specialisation

IV.I Theoretical Background: the specification

The specification we use for the analysis of spatial autocorrelation in the investment and employment specialisation 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 with available data.

The extent of investment as well as employment specialisation is – in separate estimates – explained by determinants of specialisation patterns from the traditional and the new trade theory. Locational explanatory variables are the location of a region in the economic centre[9] (CENTR) and the periphery (DIST) as well as the population density (PODEN) to capture the impact of location in the centre which is not simultaneously captured by CENTR. In addition, market potential (GRP) is important to explain specialisation in scale-intensive sectors in the core regions. Economic openness (QUINN_OPENN) is the trigger of specialisation in trade theories, however, its analysis might tell which regions are particularly affected by market integration impacts. Finally, the regional geographic size (AREA) as well as of the unemployment rate (UEWP) (approximating the regional economic performance) are added as further regional control variables.[10]

We thus have included the most important determinants which explain specialisation patterns in the analysis of Stirboeck (2004) and test the following specification for each sector:

$$\begin{aligned} SPCF(EM)EU_{ij} = {} & \beta_0 + \beta_1\, CENTR_j + \beta_2\, PODEN_j + \beta_3\, DIST_j + \beta_4\, GRP_j \\ & + \beta_5\, QUINN\_OPENN_j + \beta_6\, AREA_j + \beta_7\, UEWP_j \\ & + \textit{country dummies} + \varepsilon_{ij} \end{aligned}$$

with i (j) as the sectoral (regional) index. Since we apply a pooled regression, we omitted the time index in the above specification. Depending on the data availability for sectoral investments (employment), regressions are run for up to 45 (56) regions and up to ten years (1985 to 1994).

[9] Approximatively, it is referred to the administrative centre to capture the impact of the economic centre which is a good procedure in the countries analysed.

[10] National account data included in the analysis is based on ESA79 and taken from the Eurostat REGIO database. This refers to PODEN (in 1000 inhabitants per km²), GRP (in billions of ECU), AREA (in km²) and UEWP (unemployment rate in percent of working population). The additional variables are constructed in the following way: CENTR is a dummy set for an administrative capital, DIST is an index of peripherality measured by the distance to this administrative centre in 1000km, and QUINN_OPENN (varying from 0 to 14 by 0.5 steps) is an index of economic openness constructed by Quinn (1997) on the basis of restrictions documented by the IMF.

Since we deal with regional data and analyse the process of regional specialisation, we cannot exclude potential correlations or interactions between regional developments. Some specific regional specialisation might not be independent from the one of the neighbouring region. Spatial econometric approaches[11] explicitly model and control for spatial autocorrelation or interdependence to avoid inefficient or inconsistent parameter estimates or specification errors.

IV.II Controlling for spatial correlation and interaction in the analysis of investment specialisation patterns

In a first step, we refer to test diagnostics examining a potential spatial correlation structure in the residuals of simple OLS regressions. 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 indication of the potentially underlying structure of spatial correlation, since they are not as reliable as in case of normally distributed residuals.

The Moran I test investigates for the existence of any kind of spatial correlation, the Lagrange Multiplier (LM) error and lag tests examine the significance of a specific kind of spatial structure. Again, we conduct these tests on the basis of an inverse squared distance matrix.

Table 5: Regression diagnostics for spatial autocorrelation of investment specialisation (Regional characteristics)

	AGRO	FUEL	META	MINE	CHEM	METP	TREQ	FOOD	TEXT
Moran I	4.270 ***	-8.170 ***	-14.199 ***	10.282 ***	1.677 *	-17.373 ***	1.236	-13.249 ***	-8.452 ***
LM error test	3.958 **	31.828 ***	89.893 ***	33.774 ***	0.167	133.292 ***	0.013	80.232 ***	35.342 ***
LM lag test	17.298 ***	5.833 **	48.013 ***	53.896 ***	0.655	20.319 ***	0.043	6.762 ***	11.914 ***
	PAPE	**VARI**	**BUIL**	**TRLO**	**TRCO**	**CRED**	**OTHS**	**NMSE**	
Moran I	-3.217 ***	1.794 *	4.117 ***	10.137 ***	-1.214	6.412 ***	10.504 ***	-11.598 ***	
LM error test	7.079 ***	0.234	3.595 *	32.710 ***	1.964	11.403 ***	35.401 ***	56.981 ***	
LM lag test	1.207	6.340 **	16.434 ***	62.445 ***	6.442 **	6.653 ***	12.929 ***	6.316 **	

Table 5 presents the results of all three tests for the analysis of the determinants of sectoral investment specialisation for each of the 17 sectors. We can see that in many cases a significant structure of spatial correlation is present. The significance is not (consistently) demonstrable in the case of TREQ, CHEM as well as TRCO and only very weak for VARI. The sectoral specialisation of the regions analysed 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).

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

Paying attention to the specific kind of spatial correlation, it is mixed as well. For most sectors, the Lagrange Multiplier tests for spatial structure are significant for both, a spatial error model and a spatial lag model. Since both LM tests are sensitive against 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).[12] For nine sectors, the LM tests provide evidence of the spatial error model being the better specification. And only two services sectors (CRED and OTHS) show positive spatial autocorrelation of the error terms while the other seven sectors show a negative one.

For five sectors (being AGRO, MINE, VARI, BUIL, and TRLO) 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 specialisation of a region in one of these sectors positively influences the specialisation of the neighbouring regions in the same sector.

Table A-2 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. In those cases with higher LM error test values, the spatial error model is generally confirmed to be the best model either according to the insignificant spatial lag parameter or to the lower AIC value.

In those cases with higher LM lag test values, the results of the ML estimates are differing. Like predicted by the OLS test diagnostics on spatial autocorrelation, the spatial lag model shows a positive spatial dependence for the sectoral specialisation in MINE and TRLO. We also find a weak, positive spatial lag dependence for VARI. However, the AIC (and the likelihood ratio test value, respectively) points to a superiority of the spatial error model formulation for the two sectors AGRO and BUIL which show a positive spatial correlation structure.

The spatial parameters are insignificant – as we expected according to the OLS test diagnostics – in the estimates for CHEM (the spatial lag parameter is only significant on the 10%-level of significance while the specification is not confirmed by the LM lag test) and TREQ. The spatial error model is highly significant for TRCO, though, quite a number of coefficients included in the specification are not significant any more. Since this is the only case with evident changes in the significant variables, this rather points to a mis-specification of the spatial error model for TRCO.

Summarising, there is no significant, consistent spatial autocorrelation when analysing CHEM and TREQ. But, we can detect a positive spatial lag dependence for TRLO, MINE and VARI. However, for most other sectors, the regional specialisation underlies a spatial error autocorrelation which is negative in six cases, but positive in the other five cases. Besides the three sectors named above, we thus mostly find no spatial interdependence between the sectoral specialisation of neighbouring regions. The underlying spatial error autocorrelation instead points to potential data problems or to inadequate regional definitions what is underlined by the changing sign of the spatial autocorrelation structure.

[12] 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, so we do not include their results here.

Checking the sensitivity of the results of traditional OLS estimates, there is no general problem of significance concerning the non-spatial autocorrelation parameters. The explanatory variables which are significant in the OLS estimates are usually significant as well in the spatial estimates without changing their signs. Thus, the specialisation patterns discussed in Stirboeck (2004) are robust even when controlling for spatial autocorrelation effects.

IV.III Controlling for spatial correlation and interaction in the analysis of employment specialisation patterns

The test diagnostics on spatial autocorrelation mostly provide evidence of a significant spatial autocorrelation in the OLS estimates of employment specialisation. The Moran I test is mostly significant like for the estimates on investment specialisation – besides for the sectors BUIL and OTHS. We now only find five sectors (AGRO, TEXT, PAPE, VARI and NMSE) with a significant positive spatial autocorrelation while ten sectors (FUEL, META, MINE, CHEM, METP, TREQ, FOOD, TRLO, TRCO and CRED) show a significant negative spatial autocorrelation structure. Again, the significance of the spatial autocorrelation structure is very strong across all those sectors.

Table 6: Regression diagnostics for spatial autocorrelation of employment specialisation (Regional characteristics)

	AGRO	FUEL	META	MINE	CHEM	METP	TREQ	FOOD	TEXT
Moran I	15.523 ***	-4.943 ***	-17.355 ***	-4.873 ***	-3.874 ***	-4.921 ***	-16.924 ***	-13.737 ***	21.609 ***
LM (error) test	71.514 ***	12.887 ***	118.255 ***	12.995 ***	9.094 ***	13.359 ***	115.589 ***	77.762 ***	143.300 ***
LM (lag) test	209.153 ***	4.941 **	12.919 ***	6.759 ***	0.537	2.386	41.106 ***	7.100 ***	129.241 ***
	PAPE	**VARI**	**BUIL**	**TRLO**	**TRCO**	**CRED**	**OTHS**	**NMSE**	
Moran I	3.926 ***	13.841 ***	-0.720	-18.591 ***	-15.502 ***	-11.608 ***	-0.076	4.957 ***	
LM (error) test	2.465	55.460 ***	1.310	137.927 ***	98.340 ***	57.947 ***	0.614	4.589 **	
LM (lag) test	10.028 ***	70.362 ***	36.601 ***	82.512 ***	18.878 ***	13.613 ***	16.103 ***	55.489 ***	

Referring to the LM tests to gain insights in the specific form of spatial autocorrelation which is present, the LM lag test value is again mostly lower than the LM error test value. It is only higher with respect to AGRO, PAPE, VARI, and NMSE. It is also highly significant for BUIL and OTHS while the Moran I tests as well as the LM error tests are insignificant for these two sectors. However, these six sectors might thus be subject to significant spatial interdependencies which has to be checked in the following by discussing the spatial estimate results carefully.

In contrast to investment specialisation, we find significant spatial autocorrelation in the residuals of the estimates of all sectors when analysing employment specialisation. For those eleven sectors with higher LM error test values than LM lag test values, we can confirm a significant and consistent spatial error autocorrelation. It is negative for all of those sectors besides TEXT.

With respect to those six sectors under consideration for spatial lag dependence, the identification of the optimal model is less clear. It seems that the spatial error model is superior for PAPE and NMSE, but inferior for VARI, OTHS, BUIL and AGRO according to the AIC value[13]. While the Moran I statistics were insignificant for the sectors BUIL and OTHS, 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 underlie a positive spatial lag dependence. In economic terms, this means that regions profiting from a high specialisation in either VARI, OTHS, BUIL or AGRO exert a positive impact on the specialisation of surrounding regions in this sector.

Again, results of classical econometric estimates are mostly robust when controlling for spatial autocorrelation effects. Though we have some changes in the significance of the coefficients (in both ways, either reaching or loosing significance), the general results of the recent studies summarised in the first section can be confirmed.

V Economic Impacts of Specialisation Patterns and Determinants

The spatial econometric estimates presented above allow us to draw conclusions with respect to two main topics: robustness of previous results and spatial interaction impacts on regional specialisation patterns.

First, we find significant spatial autocorrelation effects for most sectors – independent of the analysis of investments and employment. However, these do not influence the results on the economic determinants of sectoral specialisation of EU regions.

Economic determinants do only slightly differ when comparing investment and employment specialisation as presented by Stirboeck (2004).[14] Relative investment and employment shares in manufacturing sectors are higher close to large markets, but not in the administrative centres. Consistently, relative regional specialisation in manufacturing is lower in peripheral regions while it is higher with respect to services sectors. Since market potential (GRP level) positively influences the strength of specialisation in manufacturing, we might be confronted with negative backwash effects for peripheral regions in scale-intensive manufacturing sectors.

The stronger specialisation in services sectors is evident for both, peripheral regions as well as administrative centres. However, it differs with respect to the quality of specialisation, especially for investment specialisation. Growth-oriented services sector specialisation is stronger

[13] 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.

[14] Though, there are some evident differences analysing research intensity, economies of scale as well as comparative advantage variables such as labour cost or productivity differentials. However, due to their restricted availability across time and across regions, we did not include these (though important) explanatory variables in the present analysis.

in administrative centres while tourism-related services sector specialisation is stronger in peripheral regions.

Second, though spatial autocorrelation is present, it is mostly due to spatial error autocorrelation. This is the case for the sectors FUEL, META, CHEM, METP, TREQ, FOOD, TEXT, PAPE, TRCO, CRED and NMSE – independent of the factor of production analysed. In these sectors, we have no evidence of economic interdependencies between neighbouring regions. The spatial error autocorrelation which is evident is simply an indication of potential data problems or inadequate regional definitions to capture the specific spatial dimension of sectoral specialisation patterns.

However, there are some exceptions to the prevalence of the spatial error autocorrelation with respect to some, but not all, labour-intensive sectors. Though it seems that labour-intensive production is positively influenced by the degree of specialisation of surrounding regions in some cases.

These are the sectors MINE, VARI, and TRLO with respect to investment specialisation. The regional investment specialisation in one of these three sectors is significantly and positively influenced by the one of neighbouring regions. The geographic allocation of regions specialised in these sectors shows that the highest specialisation in MINE is obvious for those regions in the central parts of Italy and in TRLO for the traditional tourist and coastal Italian regions and the isle of Corsica. No clear patterns are obvious for those regions particularly specialised in VARI.

In addition, the sectors AGRO, BUIL, OTHS and again VARI are subject to significant positive spatial interactions of employment specialisation. The spatial patterns of employment specialisation reveal that the Italian southern as well as the French western regions are marked by the highest levels of specialisation for the sectors AGRO and BUIL. A high specialisation in OTHS is evident for different regions, however, many Belgian regions, Luxembourg and some northern French regions. With respect to VARI, geographic patterns are again less clear, but a high employment specialisation is to be found in central and eastern France as well as some northern Italian regions.

VI Conclusion

Summarising, the ESDA analysis by use of the Getis-Ord statistics does not identify strong clusters of sectoral specialisation across those 56 regions included in the study. There are some few clusters (e.g. specialisation in AGRO and BUIL in Southern Italy), but these are not very striking.

In addition, we only rarely detect significant spatial interdependencies between the level of sectoral specialisation of neighbouring regions in the econometric analysis. The spatial clustering of similar sectoral specialisation in some rather unfavourable sectors in the peripheral regions identified in the ESDA analyses is not generally accompanied by significant spatial interdependencies. AGRO and BUIL are the only sectors which are marked by significant spatial interdependencies in employment (but not investment) specialisation while showing an obvious cluster in some peripheral regions. The other sectors subject to spatial interactions are clustered in different geographic locations, but not predominantly in the periphery. We thus cannot identify strong negative spill-overs or regional interactions of unfortunate specialisation patterns.

However, we have to take note that those few sectors which are subject to significant spatial interdependencies in regional specialisation patterns are rather labour-intensive and cannot be classified as strongly growth-oriented sectors. These are AGRO, MINE, VARI, BUIL, and the services sectors TRLO and OTHS.

In addition, peripheral regions are significantly stronger specialised in most services sectors as well as building & construction. Therefore, these might be affected by the positive spatial interdependencies in employment specialisation identified for BUIL and OTHS as well as in investment specialisation identified for TRLO. Depending on the nature of these activities, the spatial dependence of specialisation might demonstrate some disadvantage and low growth perspectives for those regions at a long distance to the core regions.

The specialisation in building & construction of peripheral regions reflects infrastructural activities of probably regional policy activities and not private sector activities. The specialisation in OTHS and TRLO, however, has to be evaluated more precisely. Trade and lodging can be assumed to be mostly driven by small enterprises, resulting from the mostly coastal location of these peripheral regions. Other services contain a rather broad spectrum of economic activities and is thus difficult to interpret. These include tourism-related services (like renting), but also business services (like advertising and consulting).

We might thus be confronted with some disadvantageous spatial interdependencies in the periphery. These are, however, not very strong. In addition, there is no evidence for favourable spatial interdependencies in the centre and thus no evidence for increasing core-periphery tendencies.

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Appendix:

Table A-1: 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	Lazio	LAZ	Luxembourg (B)	LUB
Champagne-Ardenne	CHA	Liguria	LIG	Namur	NAM
Corse	CRS	Lombardia	LOM	Oost-Vlaanderen	OVL
Franche-Comté	FRC	Marche	MAR	Vlaams Brabant	VBR
Haute-Normandie	HNO	Molise	MOL	West-Vlaanderen	WVL
Île de France	IDF	Piemonte	PIE		
Languedoc-Roussillon	LRO	Puglia	PUG		
Limousin	LIS	Sardegna	SAR		
Lorraine	LOR	Sicilia	SIC		
Midi-Pyrénées	MPY	Toscana	TOS		
Nord - Pas-de-Calais	NPC	Trentino-Alto Adige	TAA	**Monoregional Countries**	
Pays de la Loire	PDL	Umbria	UMB	Danmark	DEN
Picardie	PIC	Valle d'Aosta	VAO	Ireland	IRE
Poitou-Charentes	POI	Veneto	VEN	Luxembourg	LUX
Provence-Alpes-Côte d'Azur	PAC				
Rhône-Alpes	RAL				

Table A-2: Spatial Econometric Analysis (Spatial Lag and Spatial Error Model) of Investment Specialisation Patterns

	AGRO			FUEL			META			MINE			CHEM		
OLS/Spatial Lag/Error	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**
W_SPCFEU		0,428 ***			-0,503 **			-1,369 ***			0,678 ***			0,110	
CONSTANT	3,664 ***	2,958 ***	4,514 ***	-0,387	0,204	-0,868 **	3,532 ***	5,644 ***	5,582 ***	1,903 ***	0,937 **	1,641 ***	0,398 *	0,334	0,352
CENTR	-0,715 ***	-0,851 ***	-0,725 ***	0,609 ***	0,779 ***	1,417 ***	-1,372 *	-1,809 ***	-2,130 ***	-0,851 ***	-1,032 ***	-1,003 ***	-0,551 ***	-0,544 ***	-0,479 ***
PODEN	-6,882 ***	-7,526 ***	-7,366 ***	-1,328 *	-1,323 *	-0,372	-4,319 **	-4,477 **	-11,191 ***	-1,355 **	-1,525 ***	-1,344 ***	-0,430	-0,450	-0,554
DIST	-1,071 ***	-1,101 ***	-0,537 ***	0,174	0,260	0,447 ***	-0,740	-1,121 **	-0,939 **	-0,720 ***	-0,742 ***	-0,649 ***	-0,329 ***	-0,331 ***	-0,388 ***
GRP	0,012 ***	0,015 ***	0,015 ***	0,001	0,001	0,001	0,014 *	0,016 **	0,039 ***	0,004 *	0,005 **	0,004 **	0,005 ***	0,004 ***	0,004 ***
QUINN_OPEN	-0,014	-0,024	-0,030	0,096 ***	0,099 ***	0,096 ***	-0,070	-0,086	-0,167 **	0,003	0,000	0,002	0,009	0,009	0,012
AREA	-0,021 ***	-0,024 ***	-0,021 ***	0,012 **	0,011 *	0,015 ***	-0,059 ***	-0,074 ***	-0,126 ***	0,000	-0,001	-0,004	-0,002	-0,002	0,000
UEWP	0,066 ***	0,053 ***	0,011	0,097 ***	0,117 ***	0,105 ***	-0,012	-0,029	0,031	-0,010	-0,001	-0,002	0,010 **	0,011 **	0,016 ***
DUM_FRA	-1,331 ***	-0,975 ***	-1,294 ***	-0,734 ***	-0,926 ***	-0,695 ***	0,470	0,955 ***	0,828 ***	-0,740 ***	-0,393 ***	-0,469 ***	-0,017	-0,026	-0,081
DUM_IRE	0,876 **	1,455 ***	1,370 ***	-2,367 ***	-2,736 ***	-3,076 ***	2,985 *	5,138 ***	7,185 ***	0,148	0,625	0,708	0,892 ***	0,847 ***	0,592 **
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 **	3,321 ***	3,996 ***	3,512 ***	0,166	0,764 **	0,628 *	0,237	0,233	0,145
LAMBDA			0,929 ***			-1,749 ***			-1,875 ***			0,799 ***			0,434 *
Breusch-Pagan test		62,55 ***	53,01 ***		53,63 ***	77,74 ***		363,81 ***	341,16 ***		106,76 ***	115,55 ***		109,36 ***	115,66 ***
LR-test		12,44 ***	17,63 ***		6,41 **	53,25 ***		37,33 ***	72,31 ***		22,34 ***	18,12 ***		0,33	0,79
LM-Error/Lag test		14,46 ***	25,09 ***		19,65 ***	2,43		0,83	29,16 ***		24,11 ***	6,55 **		1,99	36,11 ***
AIC	2,118	2,090	2,071	2,176	2,165	2,035	4,351	4,251	4,147	1,790	1,734	1,740	0,824	0,828	0,822
no. of obs.	377			377			353			361			360		

	METP			TREQ			FOOD			TEXT			PAPE		
OLS/Spatial Lag/Error	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**
W_SPCFEU		-0,462 ***			-0,032			-0,261			-0,388 *			-0,180	
CONSTANT	0,876 ***	1,214 ***	0,962 ***	0,356	0,376	0,365	0,849 ***	1,063 ***	0,915 ***	1,550 ***	2,022 ***	1,778 ***	1,291 ***	1,448 ***	1,334 ***
CENTR	-0,705 ***	-0,694 ***	-0,605 ***	-0,567 *	-0,567 *	-0,565 *	-0,872 ***	-0,883 ***	-1,164 ***	-1,786 ***	-1,702 ***	-1,451 ***	-0,465 **	-0,435 **	-0,174
PODEN	-0,010	0,094	0,132	-0,982	-0,960	-1,011	-1,006 ***	-0,899 **	-0,724 *	-0,959 *	-0,771	-0,597	0,083	0,117	0,227
DIST	-0,377 ***	-0,358 ***	-0,267 ***	-0,840 ***	-0,849 ***	-0,838 ***	-0,897 ***	-0,948 ***	-1,033 ***	-0,695 ***	-0,608 ***	-0,644 ***	-0,621 ***	-0,646 ***	-0,598 ***
GRP	0,003 ***	0,003 ***	0,002 ***	0,004	0,004	0,004	0,003 **	0,003 **	0,002 *	0,011 ***	0,010 ***	0,007 ***	0,001	0,001	0,000
QUINN_OPEN	0,000	0,000	0,002	0,081 *	0,081 *	0,081 *	0,039 **	0,039 **	0,039 ***	-0,021	-0,018	-0,010	-0,005	-0,005	-0,001
AREA	0,003 *	0,003 *	-0,001	-0,015 *	-0,015 *	-0,015 *	-0,003	-0,003	-0,003	0,003	0,002	0,000	-0,002	-0,002	-0,002
UEWP	-0,035 ***	-0,045 ***	-0,043 ***	0,004	0,004	0,003	-0,012 **	-0,014 ***	-0,016 ***	-0,015 *	-0,028 ***	-0,041 ***	-0,038 ***	-0,042 ***	-0,049 ***
DUM_FRA	-0,013	0,011	0,044 ***	0,188	0,188	0,187	0,288 ***	0,341 ***	0,289 ***	-0,797 ***	-0,951 ***	-0,804 ***	0,177 ***	0,202 ***	0,191 ***
DUM_IRE	0,760 ***	0,875 ***	1,021 ***	0,425	0,419	0,432	2,055 ***	2,132 ***	2,378 ***	0,753 *	0,730 *	0,804 **	0,647	0,663	0,459
DUM_DEN	--			--			--			--			--		
DUM_LUX	0,230 *	0,168	0,103	-0,484	-0,474	-0,499	0,216	0,238	0,227	1,950 ***	1,617 ***	1,676 ***	-0,397	-0,410	-0,580 **
LAMBDA			-1,779 ***			0,024			-1,162 ***			-1,437 ***			-0,821 **
Breusch-Pagan test		35,20 ***	19,58 **		112,08 ***	111,13 ***		78,75 ***	76,59 ***		96,11 ***	133,82 ***		226,94 ***	218,75 ***
LR-test		12,82 ***	84,35 ***		0,02	0,01		2,99 *	35,25 ***		6,29 **	33,86 ***		0,74	7,48 ***
LM-Error/Lag test		26,14 ***	72,02 ***		1,40	1,40		40,15 ***	151,14 ***		0,18	111,97 ***		4,89 **	46,64 ***
AIC	-0,204	-0,234	-0,438	2,814	2,820	2,814	0,814	0,811	0,716	1,697	1,685	1,603	1,651	1,654	1,630
no. of obs.	361			353			361			360			361		

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	VARI			BUIL		
OLS/Spatial 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 ***	-0.142 ***	-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		

	TRLO			TRCO			CRED			OTHS			NMSE		
OLS/Spatial Lag/Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error
W_SPCFEU		0.866 ***			-0.449 **			-0.097 ***			0.691 ***			-0.254	
CONSTANT	0.754 ***	0.156	0.644 ***	-0.015	0.830 *	0.681 ***	0.352 ***	0.392 ***	0.338 ***	2.642 ***	1.381 ***	3.368 ***	0.481 ***	0.628 ***	0.470 ***
CENTR	0.135 **	0.205 ***	0.239 ***	1.612 ***	1.529 ***	1.556 ***	0.086 ***	0.077 **	0.086 ***	0.270 ***	0.214 **	0.035	0.120	0.102	-0.005
PODEN	0.535 ***	0.556 ***	0.512 ***	2.698 ***	2.299 ***	0.464	0.476 ***	0.473 ***	0.447 ***	1.392 ***	1.583 ***	1.404 ***	-0.528 ***	-0.533 **	-1.019 ***
DIST	0.210 ***	0.163 ***	0.160 ***	0.461 ***	0.513 ***	0.698 ***	0.016	0.009	-0.002	0.257 ***	0.332 ***	0.400 ***	0.473 ***	0.480 ***	0.462 ***
GRP	-0.002 ***	-0.002 ***	-0.002 ***	-0.011 ***	-0.010 ***	-0.001	-0.001 **	-0.001 **	-0.001 **	-0.002 **	-0.002 **	-0.001	-0.001	-0.001	0.001
QUINN_OPEN	-0.011	-0.008	-0.007	0.106 ***	0.099 ***	0.068 ***	-0.008 *	-0.008 *	-0.009 **	-0.098 ***	-0.100 ***	-0.107 ***	0.010	0.010	0.005
AREA	0.005 ***	0.005 ***	0.005 ***	0.016 ***	0.013 ***	-0.003	0.004 ***	0.004 ***	0.003 ***	0.001	0.000	0.000	-0.008 ***	-0.007 ***	-0.006 ***
UEWP	-0.025 ***	-0.014 ***	-0.011 ***	-0.026 ***	-0.029 ***	-0.029 ***	-0.010 ***	-0.011 ***	-0.008 ***	0.020 ***	0.008 **	-0.006	0.008 ***	0.009 ***	0.015 ***
DUM_FRA	-0.049 **	-0.035	-0.029	-0.341 ***	-0.453 ***	-0.275 ***	0.075 ***	0.090 ***	0.104 ***	0.153 ***	0.128 ***	0.250 ***	0.503 ***	0.568 ***	0.486 ***
DUM_IRE	--			-1.249 ***	-1.131 ***	-0.300	0.480 ***	0.501 ***	0.528 ***	--			0.199	0.212	0.086
DUM_DEN	--			--			--			--			0.473 ***	0.497 ***	0.384 ***
DUM_LUX	-0.111	-0.057	-0.040	-1.623 ***	-1.711 ***	-1.555 ***	2.448 ***	2.449 ***	2.547 ***	-0.841 ***	-0.957 ***	-0.776 ***	0.575 ***	0.681 ***	0.570 ***
LAMBDA			0.954 ***			-1.934 ***			0.836 ***			0.979 ***			-1.454 ***
Breusch-Pagan test		179.82 ***	186.18 ***		91.89 ***	143.35 ***		241.02 ***	263.41 ***		32.09 ***	28.76 ***		136.53 ***	113.24 ***
LR-test		36.34 ***	33.29 ***		5.57 **	42.41 ***		7.02 ***	12.58 ***		15.71 ***	63.83 ***		3.50 *	47.61 ***
LM-Error/Lag test		22.56 ***	1.46		3.03 *	34.71 ***		8.28 ***	2.60		35.49 ***	1.57		15.24 ***	138.98 ***
AIC	-0.430	-0.526	-0.523	1.219	1.209	1.102	-1.771	-1.785	-1.806	0.165	0.127	-0.013	0.018	0.014	-0.108
no. of obs.	358			363			363			358			377		

Table A-3: Spatial Econometric Analysis (Spatial Lag and Spatial Error Model) of Employment Specialisation Patterns

	AGRO			FUEL			META			MINE			CHEM		
OLS/Spatial Lag/Error	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**
W_SPEMEU		0.896 ***			-0.307			-0.234 ***			-0.304			0.098	
CONSTANT	1.744 ***	0.105	16.404 ***	0.098	0.165 *	0.093	1.050 ***	1.232 ***	1.164 ***	1.321 ***	1.740 ***	1.531 ***	0.279 ***	0.240 *	0.248 ***
CENTR	-0.103	-0.955 ***	-0.766 ***	0.053	0.050	0.118 **	-0.575 ***	-0.553 ***	-0.432 **	-0.450 **	-0.400 **	-0.304 *	-0.250 ***	-0.245 ***	-0.158 **
PODEN	-0.252 ***	-0.087	-0.044	-0.036 **	-0.039 ***	-0.102 ***	-0.090 *	-0.100 *	-0.163 ***	-0.104 **	-0.120 ***	-0.317 ***	-0.010	-0.014	0.056 ***
DIST	0.000 **	-0.642 ***	-0.298	0.000 ***	0.135 ***	0.198 ***	0.000	0.318 *	0.692 ***	0.000 ***	-0.502 ***	-0.572 ***	0.000 ***	-0.197 ***	-0.029
GRP	-0.017 ***	-0.014 ***	-0.013 ***	0.000	0.000	0.001 ***	0.002	0.002 *	0.003 ***	-0.002 **	-0.002 **	-0.002 **	0.003 ***	0.003 ***	0.003 ***
QUINN_OPEN	0.113 ***	0.066 **	0.057 *	0.003	0.003	0.000	-0.012	-0.014	-0.021	0.032 *	0.031 *	0.024	0.004	0.004	0.001
AREA	0.012 *	0.001	-0.001	-0.003 **	-0.003 **	-0.002 *	-0.019 ***	-0.021 ***	-0.029 ***	0.001	0.002	0.010 ***	-0.001	-0.001	-0.003 **
UEWP	0.165 ***	0.068 ***	0.053 ***	0.009 ***	0.009 ***	0.006 ***	-0.016 **	-0.020 ***	-0.028 ***	-0.011 *	-0.014 **	-0.029 ***	0.000	0.000	-0.002
DUM_FRA	-1.385 ***	-0.225 *	-0.777 ***	0.123 ***	0.139 ***	0.111 ***	0.194 **	0.271 ***	0.277 ***	-0.406 ***	-0.494 ***	-0.531 ***	0.070 **	0.061 *	0.113 ***
DUM_IRE	-0.869	2.318 ***	2.063 ***	0.243 **	0.258 **	0.187 *	1.396 ***	1.582 ***	2.024 ***	0.251	0.084	-0.390	0.289 *	0.258 *	0.440 ***
DUM_DEN	-1.274 **	0.766 *	0.425	0.019	0.035	-0.058	0.548 *	0.672 **	0.776 ***	-0.324	-0.465 *	-0.820 ***	0.048	0.028	0.085
DUM_LUX	-2.091 ***	-0.988 **	-1.322 ***	-0.004	0.018	-0.109	4.839 ***	4.791 ***	3.985 ***	0.292	0.048	-0.636 **	0.061	0.063	-0.223 **
DUM_BEL	-2.950 ***	-0.895 ***	-0.949 **	0.128 ***	0.153 ***	0.239 ***	0.393 ***	0.581 ***	0.654 ***	-0.431 ***	-0.531 ***	-0.215 ***	0.199 ***	0.185 ***	0.230 ***
LAMBDA			0.988 ***			-1.269 ***			-1.414 ***			-1.376 ***			-1.496 ***
Breusch-Pagan test		181.598 ***	232.323 ***		455.550 ***	396.535 ***		104.595 ***	84.380 ***		125.747 ***	85.120 ***		209.551 ***	109.960 ***
LR-test		146.902 ***	115.176 ***		2.744 *	19.711 ***		10.825 ***	81.105 ***		3.699 *	28.943 ***		0.366	51.509 ***
LM-Error/Lag test		188.392 ***	0.029		0.555	63.488 ***		35.364 ***	197.123 ***		0.112	83.495 ***		32.220 ***	40.388 ***
AIC	3.007	2.713	2.774	-0.628	-0.629	-0.674	1.889	1.868	1.693	1.599	1.595	1.530	-0.213	-0.209	-0.338
no. of obs.	494			425			413			418			413		

	METP			TREQ			FOOD			TEXT			PAPE		
OLS/Spatial Lag/Error	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**	**OLS**	**Lag**	**Error**
W_SPEMEU		0.126			-0.516 **			-0.208			0.792 ***			0.289 **	
CONSTANT	1.062 ***	0.941 ***	1.215 ***	0.858 ***	1.223 ***	0.966 ***	0.918 ***	1.070 ***	0.956 ***	3.987 ***	1.147 *	3.662 **	0.878 ***	0.669 ***	0.658 ***
CENTR	-0.850 ***	-0.848 ***	-0.891 ***	-0.599 ***	-0.635 ***	-0.670 ***	-0.532 ***	-0.539 ***	-0.645 ***	-3.978 ***	-4.462 ***	-4.456 ***	-0.183 ***	-0.186 ***	-0.228 ***
PODEN	0.103 ***	0.101 ***	0.057 ***	0.072	0.072 *	-0.001	0.011	0.014	0.005	0.534 ***	0.622 ***	0.701 ***	0.044 ***	0.000 **	0.001
DIST	0.000 ***	-0.434 ***	-0.298 ***	0.000 ***	-0.433 ***	-0.210 **	0.000 ***	-0.513 ***	-0.563 ***	-0.003 ***	-2.649 ***	-2.340 ***	0.000 ***	-0.399 ***	-0.407 ***
GRP	0.006 ***	0.006 ***	0.006 ***	0.004 ***	0.004	0.004 ***	0.000	0.000	0.000	0.013 ***	0.016 ***	0.018 ***	0.003 ***	0.000 ***	0.004 ***
QUINN_OPEN	-0.019 **	-0.017 **	-0.024 ***	-0.010	-0.012	-0.013	0.001	0.001	0.001	0.010	0.025	4.681	-0.015 **	-0.014 **	-0.013 **
AREA	0.003 **	0.004 **	-0.002	-0.009 **	-0.011 ***	-0.019 ***	0.002	0.002	0.001	0.020 **	0.025 ***	0.022 ***	0.001	0.000	0.002
UEWP	-0.028 ***	-0.025 ***	-0.037 ***	-0.005	-0.008	-0.008 *	-0.017 ***	-0.017 ***	-0.016 ***	-0.119 ***	-0.068 ***	-0.100 ***	-0.024 ***	-0.020 ***	-0.017 ***
DUM_FRA	0.185 ***	0.170 ***	0.240 ***	0.574 ***	0.715 ***	0.702 ***	0.442 ***	0.495 ***	0.436 ***	-1.385 ***	-0.560 ***	0.040	0.220 ***	0.171 ***	0.143 ***
DUM_IRE	0.763 ***	0.718 ***	1.175 ***	0.650 *	0.910 ***	1.383 ***	1.082 ***	1.136 ***	1.206 ***	1.201	1.966 **	2.927 ***	0.419 ***	0.340 ***	0.264 **
DUM_DEN	0.517 ***	0.503 ***	0.720 ***	0.346	0.485 *	0.742 ***	0.813 ***	0.846 ***	0.915 ***	-0.612	0.420	0.863	0.295 ***	0.255 ***	0.095 **
DUM_LUX	0.602 ***	0.653 ***	0.222 *	-0.056	-0.151	-0.576 **	0.315 ***	0.339 ***	0.211 **	0.147	2.784 ***	3.348 ***	0.018	0.059	0.059
DUM_BEL	-0.054	-0.048	-0.017	-0.019	0.016	0.032	0.156 ***	0.193 ***	0.137 ***	-2.021 ***	-0.682 ***	-0.001	0.156 ***	0.091 **	-0.095
LAMBDA			-1.263 ***			-1.199 ***			-0.952 ***			0.952 ***			0.839 ***
Breusch-Pagan test		59.594 ***	83.716 ***		73.754 ***	84.388 ***		78.341 ***	90.496 ***		157.846 ***	146.692 ***		134.212 ***	129.379 ***
LR-test		1.373	26.925 ***		15.034 ***	50.929 ***		3.232 *	32.050 ***		52.460 ***	67.145 ***		6.340 **	23.271 ***
LM-Error/Lag test		47.915 ***	88.465 ***		0.017	163.045 ***		24.752 ***	114.541 ***		55.413 ***	24.655 ***		5.673 **	51.590 ***
AIC	0.011	0.012	-0.054	1.519	1.488	1.397	-0.250	-0.253	-0.327	3.331	3.210	3.170	-0.512	-0.522	-0.567
no. of obs.	416			417			418			418			418		

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	VARI			BUIL		
OLS/Spatial 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	-1.325 ***	-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		

	TRLO			TRCO			CRED			OTHS			NMSE		
OLS/Spatial Lag/Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error	OLS	Lag	Error
W_SPEMEU		-0.950 ***			-0.488 **			-0.136 ***			0.312 ***			-0.698 ***	
CONSTANT	1.662 ***	3.002 ***	1.605 ***	0.844 ***	1.313 ***	0.871 ***	0.219 ***	0.280 ***	0.242 ***	0.667 ***	0.436 ***	0.648 ***	0.775 ***	1.592 ***	0.604 ***
CENTR	0.066	0.042	0.108 **	0.347 ***	0.319 ***	0.397 ***	0.234 ***	0.224 ***	0.213 ***	0.303 ***	0.330 ***	0.335 ***	0.781 ***	0.731 ***	0.706 ***
PODEN	-0.005	0.016	0.004 ***	-0.036 **	0.000 **	0.000 *	0.250 ***	0.245 ***	0.243 ***	0.000	-0.006	0.003	-0.085 ***	-0.077 ***	-0.061 ***
DIST	0.000 ***	0.394 ***	0.327 ***	0.000 ***	0.211 ***	0.263 ***	0.000	0.015	0.017	0.000 ***	0.156 ***	0.174 ***	0.000 ***	0.158 ***	0.249 ***
GRP	-0.001 **	0.000	0.000	0.001 ***	0.000 ***	0.000 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	-0.003 ***	-0.003 ***	-0.003 ***
QUINN_OPEN	-0.015 ***	-0.017 ***	-0.016 ***	0.004	0.002	-0.001	0.000	0.000	-0.001	-0.009 ***	-0.008 ***	-0.009 ***	0.021 ***	0.024 ***	0.022 ***
AREA	-0.002 **	-0.002 **	0.000	-0.005 ***	0.000 ***	0.000 ***	0.002 ***	0.001 ***	0.003 ***	0.000	0.000	0.001	0.000	0.000	-0.001
UEWP	-0.011 ***	-0.015 ***	-0.012 ***	-0.007 ***	-0.010 ***	-0.012 ***	-0.006 ***	-0.007 ***	-0.008 ***	-0.003 ***	-0.002 **	-0.003 ***	0.020 ***	0.027 ***	0.023 ***
DUM_FRA	-0.295 ***	-0.454 ***	-0.308 ***	0.027	0.017	0.023	0.155 ***	0.177 ***	0.145 ***	0.252 ***	0.191 ***	0.251 ***	0.033	0.077 ***	0.040
DUM_IRE	0.055	-0.031	-0.083	-0.078	-0.043	-0.100	0.148 ***	0.188 ***	0.120 ***	-0.603 ***	-0.694 ***	-0.641 ***	-0.414 ***	-0.353 ***	-0.272 ***
DUM_DEN	-0.357 ***	-0.436 ***	-0.478 ***	-0.059	-0.054	-0.157 **	0.181 ***	0.211 ***	0.164 ***	-0.370 ***	-0.442 ***	-0.397 ***	0.334 ***	0.432 ***	0.434 ***
DUM_LUX	-0.113	-0.286 ***	-0.301 ***	-0.230 **	-0.229 **	-0.221 ***	1.089 ***	1.091 ***	1.008 ***	-0.035	-0.108 **	-0.182 ***	-0.903 ***	-0.371 ***	-1.281 ***
DUM_BEL	-0.125 ***	-0.176 ***	-0.072 ***	0.008	0.000	0.040 *	0.164 ***	0.215 ***	0.182 ***	0.414 ***	0.318 ***	0.442 ***	0.377 ***	0.501 ***	0.403 ***
LAMBDA			-1.589 ***			-1.574 ***			-1.452 ***			-0.733 **			0.945 ***
Breusch-Pagan test		60.624 ***	72.810 ***		95.820 ***	79.322 ***		63.845 ***	75.161 ***		49.522 ***	79.063 ***		201.816 ***	111.626 ***
LR-test		50.352 ***	138.853 ***		9.059 ***	94.779 ***		13.641 ***	61.112 ***		12.914 ***	5.300 **		54.358 ***	65.563 ***
LM-Error/Lag test		2.260	16.379 ***		34.273 ***	69.720 ***		31.808 ***	0.836		38.744 ***	40.698 ***		123.005 ***	66.555 ***
AIC	-0.904	-1.020	-1.238	-0.545	-0.562	-0.772	-2.627	-2.655	-2.774	-1.956	-1.982	-1.968	-0.761	-0.884	-0.915
no. of obs.	416			416			416			418			425		