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SPECIALIZATION AND RISK SHARING: EVIDENCE FROM EUROPEAN REGIONS

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SOMMARIO

Dalla teoria economica è noto che i meccanismi di assicurazione contro il rischio di produzione (*risk sharing*) permettono un maggiore sfruttamento dei benefici derivanti dai vantaggi comparati e dalle economie di scala. Utilizzando dati per le regioni dell'UE15, si mostra come sussista in effetti una relazione positiva tra gli indici di *risk sharing* e di specializzazione industriale. Differenziandosi dalla precedente letteratura, questo lavoro verifica (e rifiuta) l'assunzione di omogeneità negli indici di *risk sharing* tra le unità geografiche. Tali stime regionali del grado di *risk sharing* sono poi utilizzate come regressori in un modello di specializzazione. L'utilizzo di tecniche econometriche non parametriche additive con dipendenza spaziale permette di studiare forme funzionali non lineari ed effetti di *spillover* tra le regioni. Infine, si fornisce una discussione dei risultati empirici in riferimento al recente dibattito sulle possibili riforme strutturali da apportare alle Istituzioni europee.

1 INTRODUCTION

At the Lisbon European Council of March 2000, European Union (EU) leaders committed themselves to a ten-year strategy for the reform of Europe's product, capital and labour markets. These policies, recalled afterwards in 2004 in the revamped Growth and Stability Pact, have been designed to be effective tools to compensate for the impact of shocks hitting EU economies and their regions. With competition induced by growing integration of markets and liberalization of capital flows, an increasingly similarity of economic systems is expected to be achieved (Frankel and Rose, 1998). More generally, factor mobility and an effective central redistributive system (for instance, Structural and Cohesion Funds programmes) might act as inter-regional insurance mechanisms and, thus, "protect" the European economic environment against idiosyncratic shocks, even in the presence of diverging economic structures.

Other observers from academic and political circles disagree with these conclusions and posit that economic integration is likely to bolster asymmetric developments and differences in growth rates across economies. The theoretical base is provided by international trade models, where economic integration is expected to promote higher specialization by exploiting comparative advantages in technology or endowments or throughout economies of scale and agglomeration effects (Helpman and Krugman, 1985; Krugman, 1991; Fujita et al., 1999), leading, thus, higher vulnerability to idiosyncratic shocks.

On the grounds of these theoretical disputes, however, assessing the ultimate effects of economic integration on the patterns of the spatial location of economic activity and their concentration across sectors is of a predominantly empirical nature. In recent years, a number of studies have focused on explaining specialization patterns in European regions (Molle, 1997; Hallet, 2002) and their effects on income inequality (Ezcurra et al., 2004) and on economic growth (Morelli, 2007). Yet to date, there has been no comprehensive study on the nexus between degree of specialization and cross-regional insurance in the context of the European regions. This paper is an attempt to fill this gap.

Understanding whether the integration process guarantees a sizable degree of cross-regional insurance is of primary importance for academics and policy makers. As suggested by the predictions of theoretical models of Greenwood and Jovanovic (1990), Acemoglu and Zilibotti (1997) and Feeney (1997), specialization may have potentially relevant consequences in boosting economic growth. Thus, empirical evidence on the relationship between specialization and insurance may question the very foundations of this class of theoretical contributions. Furthermore, finding that better insurance of production risk entails higher specialization in production may provide pervasive argumentations in favoring the evolution of the European financial system towards a paradigm with greater reliance on

capital markets as a source of funding and risk mitigation and away from all-encompassing bank intermediation.

Our investigation is intimately related to the paper by Kalemli-Ozcan et al. (2003), which represents, to the best of our knowledge, the unique empirical evidence on the relationship between industrial specialization and degree of cross-regional insurance to date. By adopting a three-stepped empirical strategy, these authors provide a measure of the degree of insurance among members (regions or countries) of a number of risk sharing groups, calculate an index of industrial specialization for each member within a group, and test whether data support a positive relationship between degree of insurance within a group and specialization. Using both income- and consumption-based measures of insurance and controlling for possible endogeneity bias as well as for other regressors that might potentially affect specialization, they demonstrate that this relation is positive, statistically significant and robust with respect to a number of alternative specifications of the empirical design.

The critical difference between the work cited above and our study is three-fold. First, we choose a genuine regional perspective so as to asses whether risk sharing and industrial specialization measures are positively related. We argue that the need for cross-regional insurance mechanisms in the presence of an ongoing process of economic integration in Europe is more critical at a regional (NUTS2) level according to two main considerations: i) even in the presence of a well established empirical regularity of little international risk sharing (the so-called "home bias" phenomenon pointed out firstly by French and Poterba, 1991), cross-regional insurance mechanisms may hold at a less aggregate level, since the degree of social and economic cohesion within countries is probably higher than between countries (Cochrane, 1991); ii) regional economies are more vulnerable to external shocks and the probability that sector-specific shocks are asymmetric is much higher at a regional level (De Nardis et al., 1996). Second, unlike previous works (Asdrubali et al. 1996; Sørensen and Yosha, 1998; Kalemli-Ozcan et al. 2003), we allow for possible heterogeneity in absorbing production risk across regional units. As widely documented in the empirical literature, structural characteristics of regional economies are much more differentiated than countrywide economic systems, so that even the average productive structures of two countries appear similar, regional specialization patterns may heavily differ. To a similar extent, their capabilities in buffering production risk are expected to vary across regions. The estimates will show, in fact, that the assumption of parameter homogeneity in the regression used to obtain region-specific measures of risk sharing is strongly rejected, albeit clear country patterns are detected. Third, in our empirical model of regional specialization we allow for both spatial externality effects and nonlinearity in the functional form of the regression equations. On the one hand, there is widespread consensus among economic theorists that market proximity affects decisions on industrial location and productive specialization, calling for a modelling approach able to capture possible linkages among

regions so as to take into account the spatial dimension of the problem (Midelfart-Knarvik et al., 2001). On the other hand, we cannot assume that the effect of risk sharing and of the other determinants of regional specialization is globally linear. For example, the literature (Kalemli-Ozcan et al. 2003; Imbs and Wacziarg, 2003; Ezcurra et al., 2004) suggests the existence of a strong nonlinearity between specialization and the degree of regional development measured by per capita GDP levels. Furthermore, abandoning the assumption of global linearity not only allows to avoid possible misspecification problems but also to shed light in nonlinearity and interaction effects which could be useful to sharpen our understanding of specialization patterns across European regions.

The paper is structured as follows. After this Introduction, we present the possible causative determinants of industrial specialization patterns in Section 2. Next, we illustrate in Section 3 data sources and the variables involved in the empirical model as well as details on our estimated region-specific measures of risk sharing . The econometric methodology and estimation results are presented in Section 4. Final remarks and bibliographic notes conclude.

2 DETERMINANTS OF SPECIALIZATION PATTERNS

While the role of cross-regional insurance mechanisms as a possible driver of industrial specialization has been neglected up to the paper by Kalemli-Ozcan et al. (2003), other causative factors have been widely employed in this strand of literature. In keeping with the most recent empirical contributions, we include measures of uninsurable risk, economic development, size of the economy and the share of manufacturing sector as further controls in explaining the sector concentration of regional productive structures in Europe. Here is a discussion of the candidate explanatory forces which are expected to be relevant for the purpose of our analysis.

Risk sharing vs self insurance. Economic theory points out that pursuing risk sharing makes it possible to benefit of new economic opportunities (Obstfeld, 1994; Murdoch, 1995) and comparative advantages (Helpman, 1981). When individuals are unable to borrow or insure, indeed, they tend to increasingly mitigate risk choosing safer production techniques or forsaking specialization towards a more sectorally diversified bucket of productions (self-insurance). By contrast, well-functioning cross-regional insurance markets constitute a central mechanism to smooth idiosyncratic shocks without necessarily implying self-insurance. A first channel to achieve cross-regional insurance is the existence of an efficient system of redistributive fiscal transfers (such as unemployment benefits and other types of insurance schemes), which allows to spread production risk among regions and to reach a higher degree of specialization by exploiting otherwise idle comparative advantages. For instance, in the US when income in a region falls by one dollar, disposable income falls by 60 cents, where the difference is due to Federal government transfers (Sala-i-Martin and Sachs, 1992). Finance

literature suggests portfolio diversification as another viable channel to insure against asymmetric shocks. If interregional and international capital markets are well integrated, both ex-ante and ex-post inter-regional insurance may operate (Asdrubali et al., 1996): while the former involve holding debt or equity claims to the output of productive assets in other country/regions, ex-post adjustment of asset portfolios concerns borrowing and lending on inter-regional credit markets in response to shocks. As pointed out by Mélitz (2004), however, broadening the concept of risk sharing to include credit markets is theoretically controversial since this form of insurance takes place after the realization of the shock. This criticism notwithstanding, in a number of previous works such a broader interpretation has been adopted (see, Kraay and Ventura, 2002, among others).

Uninsurable risks. Kalemli-Ozcan et al. (2003) point out that in the case of complete markets and a number of technologies (at least) equal to the one of regions, full risk sharing can be achieved. Under the hypothesis of no aggregate uncertainty, that is when technologies do not share common shocks, indeed, every region can eliminate GDP variability altogether. Accordingly, each region will specialize in a different technology in order to fully exploit the economies of scale in production. Given that assumption, regional income and consumption will be non-stochastic. By contrast, when only partial cross-regional insurance can be achieved, it is reasonable to expect a negative association between the degree of uninsurable production risk and specialization indexes.

The degree of economic development. A recent body of literature posits that specialization is likely to change over the development path in a non-monotonic way. In Imbs and Wacziarg (2003), the link between overall specialization and the level of income per capita follows a U-shaped pattern: at low levels of per capita income economies are forced to specialize in natural resources; subsequently they diversify (reducing their degree of overall specialization) but re-specialize once a (relatively high) level of income per capita is reached. Such a finding can be rationalized within models featuring stages of specialization, which are endogenous to both trade and economic growth (Saint-Paul, 1992). By contrast, Kim (1995) documents an inverted U-shaped relationship for the US regions: in the early stages of national growth a steady increase in regional specialization is observed; after that a decrease in specialization takes place. De Benedictis et al. (2006) reach similar conclusions, finding that specialization is negatively related to the level of development only above a certain threshold of income per capita. These studies suggest two considerations: first, the relationship between specialization measures and income per capita levels is likely to be nonlinear; second, the shape of such nonlinearity is ambiguous and, thus, it should be object of empirical scrutiny.

The size of the economy. From a theoretical perspective, the nexus between size of an economy and its degree of specialization is less than clear. In accordance with the message of the new economic geography paradigm (Krugman, 1991; Venables, 1996; Fujita et al., 1999), indeed, while agglomeration economies (such as market size effects) may promote

diversification throughout the attraction of different industries to larger regions, there may be counterforces at work in certain sectors, which would tend to increase the level of specialization in larger regions. Kalemli-Ozcan et al. (2003), instead, justify a negative effect of economic dimension on the grounds of demographic argumentations (for instance, heterogeneity of the population) as well as within-region geophysical characteristics (that is climate, landscape, and natural resources). Admitting a possible role for the latter class of factors would be also consistent with the idea of regional productive structures, which depend on their natural endowment, at least in their early stage of development (Imbs and Wacziarg, 2003). The empirical evidence is mixed as well, with estimation findings depending on the methodology adopted and on the dataset used. For instance, Kalemli-Ozcan et al. (2003) and Ezcurra et al. (2004) find that the expected negative relationship is empirically confirmed; by contrast, Imbs and Wacziarg (2003) document that the size of the economy does not exert a role in explaining specialization patterns.

The share of the manufacturing sector. A further candidate explanatory variable is the share of manufacturing on total output. Along the lines of reasoning in Imbs and Wacziarg (2003), the "specialization-diversification-specialization" sequence is likely to imply different relative contribution of economic sectors to output formation. While early stages of development should be characterized by the dominance of the primary sector, the diversification "era" of development, in the absence of risk sharing mechanisms at work, presumes the secondary sector as main driving force until the shift towards a service-based economy occurs. This argumentation thus suggests a negative relationship between specialization measures and share of the secondary sector on total output.

3 DATA SOURCES AND VARIABLE CONSTRUCTION

Three caveats should be addressed before starting the econometric investigation. *First*, in the empirical literature, various indicators of specialization have been proposed. None of these measures can be said to be optimal, however. For instance, Imbs (2001) uses a correlation coefficient between sectorial shares in aggregate output or employment, Amiti (1999) and Kim (1995) employ the Gini index, while Krugman (1991) and Clark and van Wincoop (2001) resort a Herfindahl index of concentration. See Combes and Overman (2003) for a detailed discussion on specialization measures. *Second*, several candidate observational variables (such as value added, export and employment) can be taken into account. While the use of employment shares implies observing specialization from the input standpoint, the choice of production quantities (value added or export) means taking an output-based perspective. *Third*, the scale of the spatial unit of analysis may also be of importance (Ezcurra et al., 2004; Midelfart-Knarvik et al., 2001; Morelli, 2007).

3.1 Specialization measures

Given the alternatives, we use sector employment shares to construct an indicator of overall specialization. Employment shares are computed using annual data at the NUTS-2 level for 144 European regions belonging to the EU15 countries over the period 1995-2005. Table 1 below presents the list of regions.

AT	**Austria**	ES23	La Rioja	GR12	Kentriki Makedonia	NL13	Drenthe
AT11	Burgenland	ES24	Aragón	GR13	Dytiki Makedonia	NL21	Overijssel
AT12	Niederösterreich	ES30	Communidad de Madrid	GR14	Thessalia	NL22	Gelderland
AT13	Wien	ES41	Castilla y León	GR21	Ipeiros	NL31	Utrecht
AT21	Kärnten	ES42	Castilla-la Mancha	GR22	Ionia Nisia	NL32	Noord-Holland
AT22	Steiermark	ES43	Extremadura	GR23	Dytiki Ellada	NL33	Zuid-Holland
AT31	Oberösterreich	ES51	Cataluña	GR24	Sterea Ellada	NL34	Zeeland
AT32	Salzburg	ES52	Communidad Valenciana	GR25	Peloponnisos	NL41	Noord-Brabant
AT33	Tirol	ES53	Illes Balears	GR30	Attiki	NL42	Limburg (NL)
AT34	Vorarlberg	ES61	Andalucia	GR41	Voreio Aigaio	**PT**	**Portugal**
BE	**Belgium**	ES62	Región de Murcia	GR42	Notio Aigaio	PT11	Norte
BE10	Région de Bruxelles-Capitale	**FI**	**Finland**	GR43	Kriti	PT15	Algarve
BE21	Prov. Antwerpen	FI13	Itä-Suomi	**IE**	**Ireland**	PT16	Centro (PT)
BE22	Prov. Limburg (B)	FI18	Etelä-Suomi	IE01	Border, Midlands and Western	PT17	Lisboa
BE23	Prov. Oost-Vlaanderen	FI19	Länsi-Suomi	IE02	Southern and Eastern	PT18	Alentejo
BE24	Prov. Vlaams Brabant	FI1A	Pohjois-Suomi	**IT**	**Italy**	**SE**	**Sweeden**
BE25	Prov. West-Vlaanderen	FI20	Åland	ITC1	Piemonte	SE01	Stockholm
BE31	Prov. Brabant Wallon	**FR**	**France**	ITC2	Valle d'Aosta/Vallée d'Aoste	SE02	Östra Mellansverige
BE32	Prov. Hainaut	FR10	Île de France	ITC3	Liguria	SE04	Sydsverige
BE33	Prov. Liège	FR21	Champagne-Ardenne	ITC4	Lombardia	SE06	Norra Mellansverige
BE34	Prov. Luxembourg (B)	FR22	Picardie	ITD1	TAA	SE07	Mellersta Norrland
BE35	Prov. Namur	FR23	Haute-Normandie	ITD3	Veneto	SE08	Övre Norrland
DE	**Germany**	FR24	Centre	ITD4	Friuli-Venezia Giulia	SE09	Småland med öarna
DE11	Baden-Württemberg	FR25	Basse-Normandie	ITD5	Emilia-Romagna	SE0A	Västsverige
DE21	Bayern	FR26	Bourgogne	ITE1	Toscana	**UK**	**United Kingdom**
DE50	Bremen	FR30	Nord - Pas-de-Calais	ITE2	Umbria	UKC1	North East
DE60	Hamburg	FR41	Lorraine	ITE3	Marche	UKD1	North West (including Merseyside)
DE71	Hessen	FR42	Alsace	ITE4	Lazio	UKE1	Yorkshire and The Humber
DE91	Niedersachsen	FR43	Franche-Comté	ITF1	Abruzzo	UKF1	East Midlands
DEA1	Nordrhein-Westfalen	FR51	Pays de la Loire	ITF2	Molise	UKG1	West Midlands
DEB1	Rheinland-Pfalz	FR52	Bretagne	ITF3	Campania	UKH1	Eastern
DEC0	Saarland	FR53	Poitou-Charentes	ITF4	Puglia	UKI1	London
DEF0	Schleswig-Holstein	FR61	Aquitaine	ITF5	Basilicata	UKJ3	South East
DK00	**Denmark**	FR62	Midi-Pyrénées	ITF6	Calabria	UKK1	South West
ES	**Spain**	FR63	Limousin	ITG1	Sicilia	UKL1	Wales
ES11	Galicia	FR71	Rhône-Alpes	ITG2	Sardegna	UKM1	Scotland
ES12	Principado de Asturias	FR72	Auvergne	**LU00**	**Luxembourg (Grand-Duché)**	UKN0	Northern Ireland
ES13	Cantabria	FR81	Méditerranée	**NL**	**Netherland**		
ES21	Pais Vasco	**GR**	**Greece**	NL11	Groningen		
ES22	Communidad Foral de Navarra	GR11	Anatoliki Makedonia, Thraki	NL12	Friesland		

Table 1 List of regions.

We use employment data rather than production data, because they are less sensitive to valuation problems. Moreover, such a choice has been driven by a data availability problem. Eurostat Regio dataset provides indeed information on the number of employees at two-digit level of the classification of economic activity for the period 1995-2005. The list of sectors is reported in Table 2. Any other source of data (such as, for instance, Cambridge Econometrics) provides employment or GVA regional data at a more aggregate sectoral level and/or over a shorter temporal window.

da	Manufacture of food products; beverages and tobacco
db	Manufacture of textiles and textile products
dc	Manufacture of leather and leather products
dd	Manufacture of wood and wood products
de	Manufacture of pulp, paper and paper products; publishing and printing
df	Manufacture of coke, refined petroleum products and nuclear fuel
dg	Manufacture of chemicals, chemical products and man-made fibres
dh	Manufacture of rubber and plastic products
di	Manufacture of other non-metallic mineral products
dj	Manufacture of basic metals and fabricated metal products
dk	Manufacture of machinery and equipment n.e.c.
dl	Manufacture of electrical and optical equipment
dm	Manufacture of transport equipment
dn	Manufacturing n.e.c.

Table 2 List of sectors.

Our preferred specialization measure is an index of the position of the distribution of Balassa index. Such a proxy of regional specialization has the advantage of being directly derived from a measure of sectorial revealed comparative advantages (RCA) as documented by De Benedictis and Tamberi (2004). Formally:

$$y_i = -Me((E_{is} / E_s)/(E_i / E)) \qquad (1)$$

where i denote the region and the s sector; E_{is} stands for average employment in the s-th sector for the i-th region over the period 1995-2005, E_i is the average overall employment in the i-th region; E_s indicates the employment in the s-th sector in Europe, while E is the overall European employment. Since the RCA index follows an asymmetric distribution (with a fixed lower bound, 0, and a variable upper bound, (E / E_i), its median (Me) turns out to be the most appropriate indicator of the distribution position. When y_i is high (low), an economy does (not) show a comparative advantage in a large share of sectors and its productive structure is therefore (not) diversified. So, we use the opposite median as a direct measure of specialization.

Given that the y_i remains an uncommon specialization index, we report the correlation matrix of y_i along with a number of alternative measures of specialization (Table 3). All indexes are statistically significant at the 5 percent level of significance using Fisher's z

transformation, irrespective of whether the Pearson method (upper part) or the Spearman one (lower part) is taken into account.

	H	G	Ros	RS	ATK	Theil	Krugman
G	0.93						
Ros	0.95	0.98					
RS	0.88	0.97	0.96				
ATK	0.88	0.95	0.95	0.93			
Theil	0.94	0.93	0.94	0.9	0.84		
Krugman	0.76	0.77	0.77	0.76	0.72	0.72	
Median	-0.79	-0.81	-0.81	-0.79	-0.78	-0.76	-0.75
	H	G	Ros	RS	ATK	Theil	Krugman
G	0.97						
Ros	0.97	1.00					
RS	0.91	0.96	0.96				
ATK	0.87	0.93	0.93	0.91			
Theil	0.92	0.93	0.93	0.89	0.82		
Krugman	0.73	0.76	0.76	0.73	0.68	0.68	
Median	-0.77	-0.77	-0.77	-0.75	-0.72	-0.71	-0.72

Table 3 Correlation matrix of various indexes of specialization

3.2 Risk sharing measures and other variables

Annual data over the period 1980-2003 for GDP values at 1995 euros, levels of population, manufacturing and total gross value added (GVA) for our sample of 144 European NUTS2 regions are taken from the Cambridge Econometrics database. As in Kalemli-Ozcan et al. (2003), specialization measures and candidate explanatory variables are computed on partially overlapping temporal windows. Moreover, in order to limit measurement error problems in the estimation of our proxy of risk sharing, we use the longest time span available from Cambridge Econometrics data sources.

Region-specific risk sharing index. Following Asdrubali et al. (1996), an index of cross-regional insurance can be computed by estimating:

$$\Delta gdp_{it} - \Delta x_{it} = a_t + \beta \Delta gdp_{it} + \xi_{it} \qquad (2)$$

where Δ is the first difference operator, gdp_{it} is the logarithm of per capita GDP at time t for region i, α_t is a vector of time fixed effects, ξ_{it} is a vector of error terms and $i = 1,...N(=144)$ and $t = 1981,...,2003$. The values for the index of risk sharing, β, are expected to lie in the $[0,1]$ interval: when $\beta = 1$ full risk sharing is achieved; when $\beta = 0$ there is no inter-regional insurance at all. The variable x_{it} can be the logarithm of per capita personal income or per capita consumption, alternatively. In the first case, β is intended to capture ex-ante insurance mechanisms; using consumption, instead, allows for addressing ex-post inter-regional insurance. Even though both mechanisms may be relevant for specialization decisions, on the grounds of the well-documented dominance of bank-based over market-based financial markets in Europe, however, we argue that ex-post portfolio

adjustment is the most appropriate way to deal inter-regional insurance. Furthermore, the temporal slightness of regional per capita personal income data may pose some problems in computing ex-ante measures of risk sharing. Thus, in this work we focus on consumption-based measures of risk sharing.

We estimate equation (2) by Least Squares Dummy Variables (LSDV) and Seemingly Unrelated Regression (SUR) techniques. The LSDV or fixed effects coefficient β turns out to be 0.421 and significantly different from zero (at the 1 percent significance level), giving support to the risk sharing hypothesis in the case of European regions. The magnitude of β gives support to the idea of higher risk sharing taking place when smaller geographical units are taken into account (Cochrane, 1991). Although the variable intercept model accommodates spatial heterogeneity to a certain extent, it still imposes the restriction of common slopes for all the regional units. Thus, we investigate the impact of the cross-sectional heterogeneity on the LSDV results by estimating N separate equations by OLS, with the observations stacked by spatial unit over time (under the assumption that slope parameters β_i are fixed distributed between spatial units). Even though the unconstrained model appears as the most suitable for estimation of model (2),[1] the OLS estimations may be affected by cross-sectional correlation. Thus, in order to increase the efficiency of the estimates, we make use also of SUR techniques. Such a specification is reasonable when the error terms for different spatial units, at a given point in time, are likely to reflect some common immeasurable or omitted factor. In all entities of reference, the estimated parameters turn out to be statistically different from zero at the 5 percent significant level or better, with an estimated average value of β equal to 0.528. Finally, the correlation coefficient between OLS-based and SUR-based estimates of risk sharing is remarkably high (0.919) and statistically significant at the 1 percent level. Figure 2a reports the regional distribution of SUR coefficients β_i. Higher values are concentrated in Italy, Austria, Ireland and Luxemburg and lower values concentrated in Spain, Portugal, France and The Netherlands: a country pattern is therefore clearly evident.

Other candidate determinants of specialization. Besides a regional risk-sharing index, our set of candidate explanatory variables includes a number of regressors, whose construction is detailed below. These variables are constructed as averages of yearly observations over the period 1980-2003. Following Kalemli-Ozcan et al. (2003), a measure of uninsurable risk, vol_i, is given by the standard deviation of the first differences of the logarithm of GDP. In keeping with a number of empirical works (Kalemli-Ozcan et al., 2003; De Benedictis et al., 2006; Imbs and Wacziarg, 2003; Ezcurra et al., 2004), we employ gdp_i as a proxy for the degree of economic development. We also include regional population, pop_i, so as to measure regional size. Finally, the share of the manufacturing sector on total GVA is defined

[1] The F-test rejects the null hypothesis of common slopes (the value of the F statistics is 4.154, with a the p-value of 0.000). The magnitude of statistically significant coefficients ranges from 0.157 to 1.000. The average of the estimated parameters is 0.521, which is quite close to the corresponding LSDV parameter.

as $man_i = \ln(GVM_i / GVA_i)$, where GVM_i and GVA_i indicate regional GVA in the manufacturing sector and total GVA, respectively.

Further controls. a) In order to control for possible unobservable country-specific factors, we include fourteen country dummies as additional regressors. These are binary variables, which take value 1 if a region belongs to a certain country and 0 otherwise. b) As further regressors, used in the robustness checks discussed in Section 4 below, we also construct the share of the agricultural sector, agr_i, and of the mining sector, min_i, on total GVA, in a similar way to the one followed to obtain man_i, *mutatis mutandis*. c) Finally, in our econometric investigation all variables are weighted by the regional population so as to reduce the possible impact of small highly specialized regions.

A picture of the distribution of the variables used in the baseline specification is provided in Figure 1. For the ease of interpretation of econometric results discussed below, all quantities are standardized, by computing the deviations from the European average and dividing by the standard deviation.

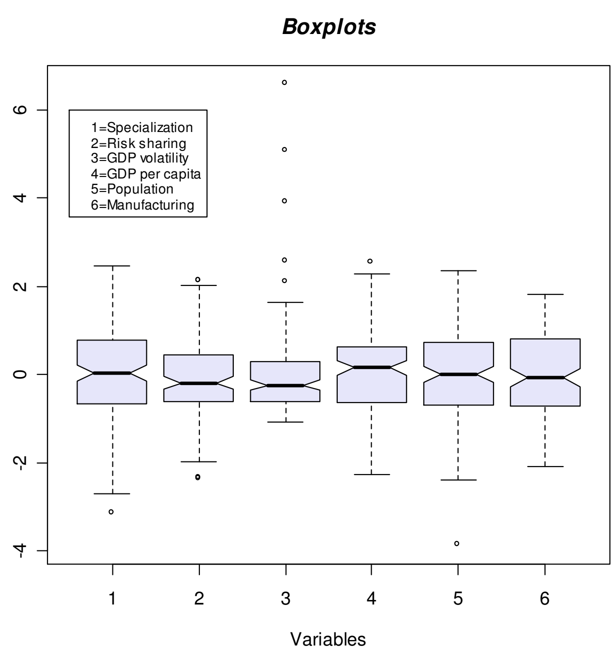


Figure 1 Boxplots

4 ESTIMATION RESULTS

Unlike previous works, our modelling approach jointly allows for nonlinearity and spatial dependence. We cannot assume indeed that all economies obey a common linear pattern. For example, the literature suggests the existence of a strong nonlinearity between specialization

and the degree of regional development measured by per capita GDP levels. From a statistical point of view, we relax the assumption of global linearity in order to avoid misspecification problems. The model is also specified so as to consider the possibility of spatial externalities, as we cannot disregard spatial contagion effects in the determination of specialization patterns.

4.1 Model specification: a semiparametric spatial autocovariance model

Nonlinearities are usually addressed by including polynomial transformations of the variables. A quadratic term for per capita GDP is usually considered in the specification of a vregional specialization model by Imbs and Wacziarg (2003) and by Kalemly-Ozcan et al. (2003). We resort, instead, a semiparametric methodology. Specifically, by using a particular version of the semiparametric model that allows for additive components, we are able to obtain graphical representation of the relationship between regional specialization and regional characteristics. Additivity ensures that the effect of each of the model predictors can be interpreted net of the effect of the other regressors, just as in linear multiple regression. A typical semiparametric additive model (AM) is specified as follows:

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \ldots + \varepsilon_i \qquad (3)$$

where ε_i is a vector of independently, identically and normally distributed errors, $\varepsilon_i \sim iidN(0, \sigma_\varepsilon^2)$, $f_j(.)$ are unknown smooth functions of the covariates, X_i^* is a vector of strictly parametric components and α^* is the corresponding parameter vector. The most popular approach for estimating AMs is the back-fitting algorithm (Hastie and Tibshirani, 1990). This method, however, presents some shortcomings with respect to model selection and inference issues. Wood (2000, 2006) and Wood and Augustin (2002) have recently proposed a new methodology to estimate AMs with spline based penalized regression smoothers which allows for automatic and integrated smoothing parameters selection via Generalized Cross Validation (GCV). Wood has implemented this approach in the R package *mgcv*.

As pointed out by Anselin (2004), spatial externalities may occur either in unmodeled effects (when unmodeled variables that are subsumed in the error term jointly follow a spatial random process) or in modelled effects (when the exogenous terms affect the left hand side of the model through a 'global multiplier effect'). Dealing with spatial externalities within a nonparametric framework is a challenging task and at the research frontier in spatial econometrics. In a parametric linear setting, such as $g = Q'\delta + \xi$, global multiplier effects are modelled by replacing Q by $(I - \rho W)^{-1}Q$ and ξ by $(I - \rho W)^{-1}\xi$, where I is an identity matrix, ρ is the parameter of spatial externality and W is a spatial weights matrix. The characteristic element of this matrix, w_{ij}, summarizes the interaction between regions i and j. Throughout the paper, the $W = \{w_{ij}\}_{i,j=1,\ldots,N}$ matrix is specified so that w_{ii} are set to zero

whereas $w_{ij} = d_{ij}^2$ if $d_{ij} < \bar{d}$ and $w_{ij} = 0$ if $d_{ij} > \bar{d}$, with d_{ij} the great circle distance between the centroids of region i and region j and $\bar{d}$ the cut-off distance (equal to 424 km). In the present context, the inverse spatial transformation of Q and ξ suggests that the attractiveness of region i is affected not only by its own characteristics and random shocks, but also by the features and random shocks of all other regions. Thus, every location is correlated with every other location in the system. However, given the characteristics of the standardized spatial weights matrix, the strength of spatial dependence between observed regions declines with the distance between them. In other words, neighboring units exhibit a higher degree of spatial dependence than units located far apart (‘*spatial diffusion with friction*’). The introduction of the spatial multiplier effect in the model yields a reduced form as $g = (I - \rho W)^{-1} Q'\delta + (I - \rho W)^{-1}\xi$ and the structural form becomes the standard spatial autoregressive model (SAR) $g = \rho W g + Q'\delta + \xi$. These arguments can be extended to the semiparametric AMs, with the obvious difference that the effect of spatial externalities may not be homogenous over space. So, model (3) can be extended by including the smooth term $f_4(Wy)$ on the right hand side (SAR-AM):

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + f_4(Wy) + \ldots + \varepsilon_i \tag{4}$$

However, because of the feedbacks between y_i and its spatial lag term Wy_i, $f_4(Wy)$ enters endogenously in equation (4), that is $f_4(Wy)$ and ε_i are correlated.[2] In linear spatial regression analysis, Kelejian and Prucha (1998) have proposed a 2SLS procedure to estimate the spatial autocorrelation regression model and have suggested to use spatial lags of the strictly exogenous variables as instruments. Following a 2SLS approach, Wy is regressed on a set of exogenous and predetermined variables. In the second stage, the fitted values from the first stage are used in place of the endogenous variable. The motivation for this form of 2SLS is the replacement of the endogenous regressor with that part of Wy (its linear projection on the set of spatial lags of the exogenous variables) that is uncorrelated with the error term. As emphasized by Blundell and Powell (2003), however, this procedure is not suitable for the estimation of nonparametric and semiparametric models. In particular, the replacement of the endogenous term with fitted values of the first stage generally yields inconsistent estimates of $f_4(Wy)$. Accordingly, they have proposed a general solution which is appropriate for the estimation of nonparametric models. This method consists of extending the “control function” method to additive nonparametric models.

The control function approach applied to a generic linear model $g_i = Q_i'\delta + \xi_i$ has its antecedent in the interpretation of the 2SLS estimator as the coefficients on Q_i in a OLS regression of g_i on Q_i and the residuals μ_i from a linear regression of Q_i on a set of

[2] The interpretation of the role of *Wy* can generate some confusion: “While it may be intuitive to interpret such a variable as relating values for *y* at *i* to its neighbours, this is only partially the case, since the neighboring values in turn depend on y_i. More precisely, the particular spatial pattern between locations and their neighbors can be considered to be the equilibrium outcome of a process that follows from global spatial correlation in the *X* and error terms. Hence, any economic interpretation of y_i depending on y_j actually works through the spatial patterns in the *X* and *u*” (Anselin, 2004, p. 6).

instruments P_i. Application of the control function approach to the semiparametric settings described above is straightforward. It consists of two steps. In the firsts one, an auxiliary nonparametric regression $Wy_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + h(Z_i) + ... + \upsilon_i$ is considered, with Z_i a set of conformable instruments and υ_i a sequence of random variables satisfying $E(\upsilon_i \mid Z_i) = 0$. Moreover, if Z_i and ε_i are independent, then it yields that $E(\varepsilon_i \mid \upsilon_i, Z_i) = E(\varepsilon_i \mid \upsilon_i)$. It follows from the last assumption that $E(\varepsilon_i \mid Wy_i) \neq 0$ arises when $E(\varepsilon_i \mid \upsilon_i) \neq 0$. The second step consists of estimating an AM of the form

$$y_i = X_i^{*'}\alpha^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + f_4(Wy_i) + f_5(\hat{\upsilon}_i)... + \varepsilon_i \quad (5)$$

Another source of bias is represented by the inclusion of variables measured with error, such as our proxy of risk sharing. Since this variable is an estimated coefficient, we cannot exclude the existence of a correlation between risk sharing and the error term. Again, the control function approach can be used to take account of this problem.

4.2 Estimation results and diagnostics tests

Table 2 reports the estimation results and a battery of diagnostics tests for a fully parametric specification of the model of regional specialization. The dependent variable measures the degree of regional specialization, computed according to the formula (1). For ease of exposition, we briefly recall the set of regressors: i) $\hat{\beta}_i$ is a proxy of region-specific risk sharing index as discussed in Section 3.2; ii) vol_i is the GDP volatility, indicating the degree of uninsured risk; iii) pop_i is the size of the region expressed in terms of log of the number of inhabitants; iv) gdp_i indicates the regional economic development level; and v) man_i the log of the share of manufacturing on total economic activity. All models include the spatial lag of the dependent variable, Wy_i, in order to control for interregional spillover effects in the process of determination of regional specialization patterns. Finally, fourteen country dummies are included in all models to control for residual spatial heterogeneity.

Since endogeneity problems may arise both from simultaneity problems and measurement errors, due to the presence of Wy_i and $\hat{\beta}_i$ in the set of covariates, we apply the control function approach. It yields to the inclusion of two additional smooth terms, $f(\hat{\upsilon}_{1t})$ and $f(\hat{\upsilon}_{2t})$, which represent the estimated residuals from two distinct first step estimations. The set of additional instruments for the two auxiliary regressions are the spatial lags of exogenous terms, an indicator of "financial depth", measured by the share of the financial and real estate sectors on total GVA, and the investor protection index provided by the World Bank.

Model A in Table 2 resembles a specification widely used in previous works, where the regression function is linear in all terms but gdp which is assumed to have a quadratic effect on y. Unlike the existent literature, however, we consider the possibility of spatial spillover. The estimation results give evidence of a significant positive effect of risk sharing on regional

specialization, corroborating the argumentations in Kalemli-Ozcan et al. (2003). Notice, however, that all other regressors are statistically not significant except for *gdp* and its square term. Furthermore, no clear spatial dependence is found, while some traces of endogeneity are detected for the risk sharing parameter. The F test for the overall significance of the additional instruments confirm the validity of our set of instruments. Furthermore, the Sargan test gives a statistics of 18.211 with a p-value of 0.442, indicating no correlation between the instruments and the error term. As for diagnostic tests, we find not only some departures from the constant variance assumption, but also from linearity. This encourages us to pursue a semiparametric modelling strategy.

	Coefficients	p-values
$\widehat{\beta}$	0.803	0.003
vol	0.055	0.721
pop	-0.063	0.828
gdp	0.450	0.000
gdp^2	0.351	0.000
man	-0.139	0.114
Wy	0.252	0.422
$\widehat{v}_1$	-0.699	0.143
$\widehat{v}_2$	-0.545	0.075
$\mathrm{R}^2 - adj.$	0.286	
Deviance	40.0	
GCV score $\times 1000$	4.711	
F test first step a)	6.653	0.000
F test first step b)	1.483	0.075
Normality	4.614	0.100
Linearity	4.589	0.012
Constant variance	1.634 (edf=2.260)	0.155

Table 2 Estimation results: Model A

Table 3 shows the results and diagnostics for three different semiparametric specifications: in Model B all terms enter nonlinearly but additively, while Models C and D allow for some interactions between variables. Allowing for nonlinearity (Model B), the model fit improves significantly: the adjusted R^2 goes from 0.29 to 0.52, the percentage of explained deviance increases from 40 to 64 percent and the GCV score (×1000) decreases remarkably from 4.711 to 3.498. The F-tests for the overall significance of the smoothed terms in Model B have p-values lower than 0.05 in five out eight cases, while the number of effective degrees of freedom (edf) suggests that the relationship between regional specialization and its determinants is far from being linear, except for $s(pop)$ and $s(\hat{\upsilon}_2)$. This more flexible specification allows to recover significance for the effect of manufacturing share and for the

spatial lag term which turns out to be strongly endogenous. The lack of significance for uninsurable risk and population suggests a possible collinearity or concurvity problem which calls for interaction effects.

Models C departs from the previous specification by considering the joint effect of insured ($\hat{\beta}$) and uninsured risk (vol) and the effect of the interaction between the size of the region (pop) and its economic development (gdp). The two interaction terms are significant at the 1 percent level and the *edf* clearly indicates nonlinear effects. The univariate smooth terms are significant and nonlinear as well. The only exception is the term $s(\hat{\upsilon}_2)$ which enters linearly but it is statistically not significant, thus ruling out any bias due to the measurement of $\hat{\beta}$'s. On the one hand, this finding gives support to our SUR-based approach for the computation of regional-specific risk sharing indexes; on the other hand, the lack of statistical significance of $s(\hat{\upsilon}_2)$ suggests excluding it from the set of covariates. Estimation results from Model D, indeed, indicate a slight improvement of the goodness of fit and a decrease of the GCV score.

	Model B			Model C			Model D		
	F test	p-values	edf	F test	p-values	edf	F test	p-values	edf
$f\left(\widehat{\beta}\right)$	2.259	0.023	4.542	.	.	.	.	.	.
$f(vol)$	1.308	0.259	2.837	.	.	.	.	.	.
$f(pop)$	1.370	0.244	1.000	.	.	.	.	.	.
$f(gdp)$	4.319	0.000	2.706	.	.	.	.	.	.
$f(man)$	2.337	0.037	2.522	3.486	0.004	2.740	3.640	0.003	2.762
$f(Wy)$	2.532	0.018	3.214	2.921	0.013	2.839	2.919	0.013	2.850
$f(\widehat{v}_1)$	6.400	0.000	3.494	5.916	0.000	4.767	5.908	0.000	4.783
$f(\widehat{v}_2)$	1.968	0.163	1.000	0.080	0.777	1.000	.	.	.
$f\left(\widehat{\beta}, vol\right)$	.	.	.	2.595	0.000	17.946	2.744	0.000	18.189
$f(pop, gdp)$	.	.	.	5.546	0.000	24.232	5.632	0.000	24.455
$\mathrm{R}^2 - adj.$		0.524			0.761			0.764	
Deviance		64.1			87.4			87.4	
GCV score $\times 1000$		3.498			2.509			2.462	
F test first step a)	15.463	0.000		15.463	0.000		16.496	0.000	
F test first step b)	1.693	0.038		1.693	0.038		.	.	
Normality	2.463	0.291		0.893	0.639		0.869	0.648	
Constant variance	0.936	0.445	1.856	0.313	0.576	1.000	0.222	0.639	1.000

Table 3 Estimation results: Models B, C and D

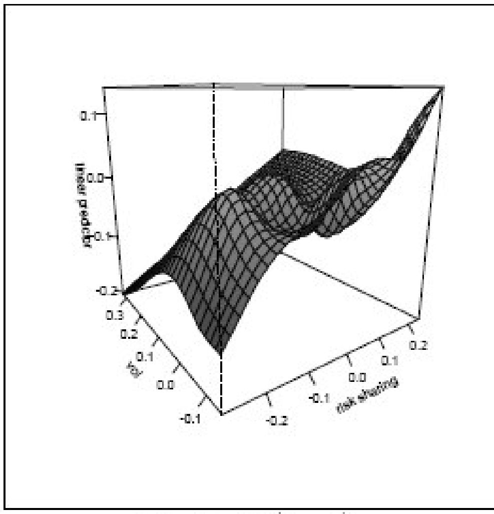
4.3 Partial effects of the smooth terms

In this Section we discuss in some details the partial effects of bivariate and univariate smooth terms estimated by using our preferred specification (Model D). Figures 2a) and 2b) show the

joint effect of risk sharing and GDP volatility - $f(\hat{\beta}, vol)$ - from two different perspectives. In each plot, the vertical axis displays the scale of the expected values of regional specialization, while the two axes of the horizontal plane report the scale of risk sharing and GDP volatility. First, we observe that the two variables interact negatively: the expected degree of specialization reaches its maximum at the highest level of risk sharing and at the lowest value for uninsured risk; the opposite holds for high levels of vol and low values for $\hat{\beta}$'s. Second, for high levels of risk sharing, GDP volatility affects negatively the degree of specialization only up to the European average; beyond this threshold, uninsured risk does not influence specialization. Conversely, when the level of risk sharing is low, the effect of vol is hump-shaped. Third, for high levels of GDP volatility, risk sharing influences specialization almost linearly, while for low levels of vol the effect of risk sharing is nonlinear, as the slope of the curve increases with increasing levels of $\hat{\beta}$. Most importantly, we can safely conclude that the effect of risk sharing is quasi-monotonically positive, in a way fully consistent with our theoretical underpinnings.

Figures 2c) and 2d) display the effect of the interaction between population and per capita GDP, $f(pop, gdp)$. The well-established U-shaped relationship between the degree of specialization and the stage of economic development (e.g. Imbs and Wacziarg, 2003) turns out to be the result of a differentiated behavior of large and small regions. When gdp is lower than the European average, the expected level of specialization is actually high for small regions. This evidence, however, does not hold when large geographical entities are considered. In this case, indeed, the degree of sectoral concentration increases with per capita GDP only at later stages of development. As for the effect of population, we observe a negative relationship with the degree of specialization, but the slope of the curve becomes steeper at higher gdp levels. This suggests that if a region is large but relatively poor in terms of per capita GDP, the heterogenous demand has to be satisfied through a diversified industrial production; when, instead, the region is relatively rich, consumers' needs are more likely fulfilled by interregional trade and, thus, comparative advantages can be better exploited.

Figures 3a) and 3b) show the fitted univariate smooth functions (solid lines) $f(man)$ and $f(Wy)$, respectively, alongside Bayesian confidence intervals (shaded gray areas), computed as suggested by Wood (2004). In each plot, the vertical axis reads as previous graphs, while the horizontal ones report the scale of manufacturing shares and the spatial autocorrelation term, respectively. A nonlinear patter for $f(man)$ emerges, with a clear downward pattern only up to a threshold corresponding to the European average: when manufacturing is a small fraction of total GVA, the regional producers necessarily concentrate in few sectors, while increasing the share of manufacturing the region becomes less specialized. Beyond the European average, the manufacturing share has no effect on the degree of specialization, since the confidence intervals become much larger.



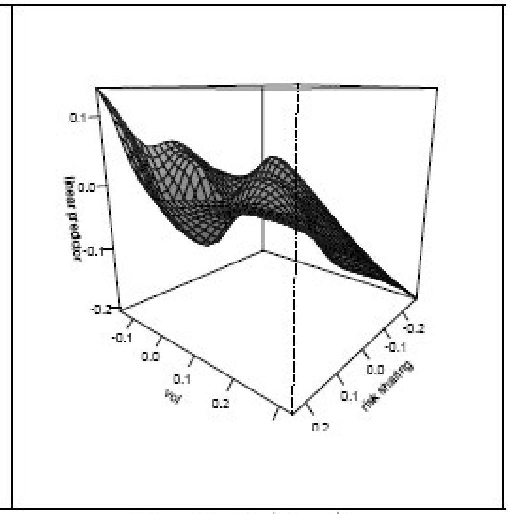
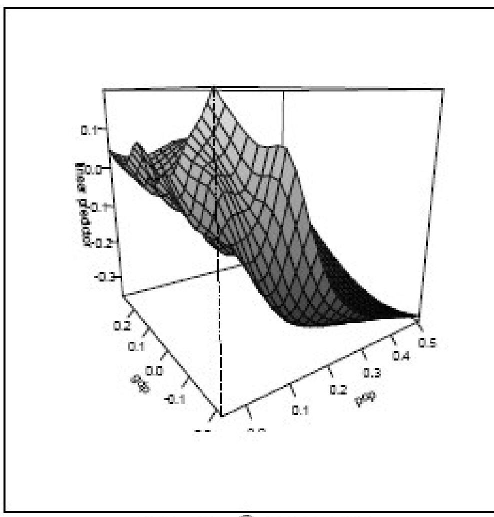


Fig. 2a - $\widehat{f}\left(\widehat{\beta}, vol\right)$ Fig. 2b - $\widehat{f}\left(\widehat{\beta}, vol\right)$



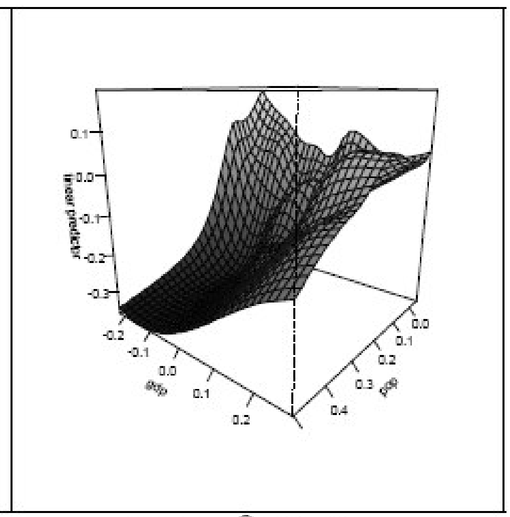


Fig. 2c - $\widehat{f}\,(pop, gdp)$ Fig. 2d - $\widehat{f}\,(pop, gdp)$

Figure 2 Bivariate smooth terms.

Positive spatial externalities are evident only beyond a threshold of Wy, corresponding to 3 percent less than the European average. As discussed above, a positive effect of Wy implies that a change in an exogenous variable - such as, for example, $f(\hat{\beta}, vol)$ - as well as a random shock in a specific region affect not only the specialization pattern of that region, but also the degree of specialization of all other regions in the EU15 system through a spatial multiplier mechanism (global spillover). Moreover, the slope of the smooth function $f(Wy)$ is always lower than |1|, as indicated by the 45-degree dashed line, suggesting that the requirement needed to avoid explosive multiplier effects is satisfied.

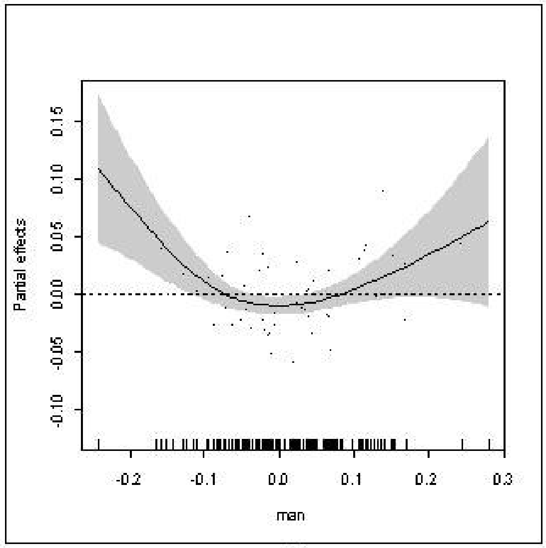


Fig. 3a - $\widehat{f}(man)$

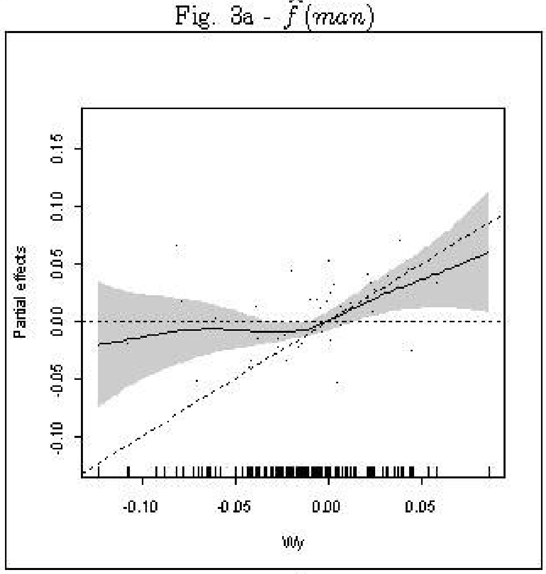


Fig. 3b - $\widehat{f}(Wy)$

Figure 3 Univariate smooth terms.

5 CONCLUSIONS AND FURTHER DISCUSSIONS

Using data on 144 European NUTS2 regions belonging to the EU15 countries, we have estimated a regional-specific measure of risk-sharing by using LSDV and SUR techniques for panel data. However, unlike previous works, we have tested the assumption of parameter homogeneity across geographical units. Albeit a clear country pattern is found, we have documented that the parameter homogeneity assumption is strongly rejected by the data. Furthermore, we have given support to the idea pointed out in Cochrane (1991), according to which substantial interregional risk sharing takes place when smaller geographical units are

taken into account: our estimates indicate that credit channel is able to insure from 40 to 50 percent of production risk, well above the empirical evidence reported in the literature hitherto. We then have exploited the cross-section heterogeneity in the risk sharing parameters, using SUR coefficients as explanatory variables in a model of regional specialization, where the dependent variable is a synthetic measure of overall specialization derived directly from detailed measures of comparative advantages. By estimating nonparametric additive spatial auto-correlated models, we have allowed for nonlinearities and spatial dependence to control for other relevant regressors for specialization patterns. Spatial autocorrelation has been modeled by including the spatial lag of the dependent variable on the right hand side of the model. Our results corroborate the hypothesis that risk sharing and the degrees of specialization of European regions are positively related. This effect, however, is strongly nonlinear: a positive partial effect of risk sharing on specialization emerges only when the level of risk sharing is above the European average.

Aside from their scientific merits, our findings have relevant policy implications. The effective role of credit markets in insuring against production risk reflects the impressive development of this financial segment in Europe. While in 1992, the European bond markets were about half the size of their US counterparts in terms of the value of debt outstanding relative to GDP, they have by now almost converged, growing from 84 percent of GDP in 1992 to 145 percent in 2004, whereas US markets grew from 150 to 175 percent (Paesani and Piga, 2007). The evidence here reported clearly suggests the desirability of further improvements in financial integration in Europe so as to cushion adverse shocks to output as well as to exploit comparative advantages and economies of scale.

As a matter of fact, ex-post insurance mechanisms can work through the fiscal channel as well. Favoring financial integration appears, however, a more viable option relative to alternative policy measures, such as relaxing the restrictions on fiscal criteria imposed by European arrangements and/or relying on the effectiveness of central redistributive mechanisms for regional output stabilization (Sørensen and Yosha, 1998). Actually, the Stability and Growth Pact was reformed in such a way to cater for a possible trade-off between reforms and budgetary discipline. However, in order to prevent moral hazard and a dilution of the Maastricht deficit threshold, the conditions under which more flexibility would be granted in exchange of reforms are tight: if government short-sightedness prevails, a "soft" application of the Pact may actually discourage rather than trigger reforms (Buti et al., 2007) . Moreover, structural changes cannot be implemented quickly but need many years for accomplishment and are really costly. Finally, the model of fiscal policy coordination adopted in Europe tends to leave the responsibility for stabilization policies prevalently up to the single Member States and merely asserts the need for coordination of fiscal policies at the European level. But the drawback is that coordination is carried out in the Council, which can only adopt recommendations and has no coercive means (Majocchi, 2003).

A fuller understanding of the relative importance of various channels for risk insurance at a NUTS2 level is an empirical question that calls for further analysis. Another venue for further investigation may take account of a wider set of European regions moving from the EU15 towards the recently enlarged EU25 context so as to assess whether inter-regional insurance mechanisms are effective tools in buffering production risk even in the presence of a larger number of backward regions. These issues are left for future research.

ABSTRACT

Economic theory emphasizes that pursuing risk sharing allows to exploit benefits from comparative advantages and economies of scale. Using a comprehensive European regional dataset, we show that risk sharing and industrial specialization indexes are, in fact, positively related. Unlike previous works we test (and reject) the assumption of parameter homogeneity across geographical units in measuring risk sharing. The estimated regional-specific index of risk sharing is then used as a covariate in a model of regional specialization. By estimating nonparametric additive spatial autocovariance models, we allow for nonlinearities and spatial dependence when we control for other relevant regressors. Finally, we discuss our empirical findings in light of the recent debate on the restructuring of European institutions.

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