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Stochastic kernel and conditioning schemes: a study about the influence of spatial factor on agriculture of EU NUTS2

[preliminary version]

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Abstract Besides to be an useful methodology for the detection of distribution dynamics of indicators, stochastic kernel methodology has been generalized to a regression-like rationale (Quah, 1997). The latter allows to determine how a distribution is influenced by a "factor", through a "conditioning scheme" which is a set of rules stating how the original distribution is altered in order to obtain its "conditioned" version.
This paper aims to study the influence of the "spatial factor" on distributions of selected agriculture impact indicators across EU NUTS2. The present work offers an empirical analysis of dynamics of selected indicators of agriculture across NUTS2. Our scope is to give an overlook of EU territorial discontinuities in order to point out time and space features related to "polarization".The paper describes and explores different space-conditioning scheme (Quah, 1997) and compares their effects over original distributions in highlighting peculiar "local" behaviors of groups of territorial units.

Keywords
Agriculture, polarization, NUTS2, spatial analysis, stochastic kernel

JEL code:
R12, Q19, C14

1. Introduction

Integration process of European economy has been characterised by two main elements. The first one is the significant tendency of productive structure to converge. On another side, territories have been characterised by sectorial discontinuity due to different infrastructural and technological endowment. In such a context the role of agricultural and agro-industrial sector has had a remarkable centrality and relevance[1]. Before both "decoupling" policy, introduced by MacSharry reform, and Agenda 2000 took place, the core of CAP (Common Agricultural Policy) was directed to support products more than farms. This turning point should be more evident in the current programming cycle 2007-2013: "the new rural development policy […] now focuses on three core objectives, namely the improvement of the competitiveness of the farming and forestry sectors, the improvement of the environment and the countryside though support for land management, and the improvement of the quality of life in rural areas and the promotion and diversification of economic activities"[2]. Articulation and differentiation of these objectives are consistent with the presence of territories yet presenting discontinuities. In this context a deeper understanding of regional disparities, dynamics, and mostly territorial effects linked with agricultural economics and rural development dynamics, appears to be necessary. Interesting remarks about this argument are passed by Léon (2005), who emphasizes the importance of rural development analysis as a relevant issue for both policy-making and mere scientific interest. The author points out the role of polarization of space, a major phenomena in contemporary economics, and the relevance of spatial dimension as explicative elements of the economics of rural areas.

The present work offers an empirical analysis of dynamics of selected indicators of agriculture across NUTS2. Our scope is to give an overlook of EU territorial discontinuities in order to point out time and space features related to "polarization". In general scholars mean the latter term as a phenomenon of clustering of "elements" around "poles" (see Esteban and Ray, 1994). Actually applied literature reports a twofold way to intend it. Studies led by Quah (1997a; 1997b) mean polarization as a shape feature of distributions showing multimodality. Many contributors have widely referred to this concept in order to characterize the distribution of world output across countries, whose dynamics shows the presence of well-detached clusters (so called "club convergence"). A second interpretation is linked with those phenomena taking place across territories (Henderson, 1988), and it is the one cited by Léon (2005) who defines "polarization of space" as something related to "the organization of areas where activities and people concentrate" (Léon, 2005, p.304).

The former definition has been adopted by a certain econometric literature on convergence (Quah 1997a; 1997b), which is said to happen when poles of a distribution collapse into unimodality. We consider it as a more general statistical issue than the second definition which is connected to those specific phenomena spreading across territories. As a matter of fact multimodality is a relevant obstacle for classical statistical parametric inference to take place. When the latter techniques are applied on a polarized distribution a parameter could not be able to catch and synthesize the behavior of the hypothetical average unit, since its role itself of being representative of a phenomenon showing a tendency to form local clusters is put under discussion.

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[1] European Commission (2007), p.9

[2] *Ibidem*, p.8

A further issue concerns a distribution-polarized phenomenon taking place across a territory. Spatial econometrics widely discusses about concentration and agglomeration of “events”, and models which explain it in the most opportune way.
After all, the two questions can merge in order to analyze those case studies where space plays an important role in characterizing polarized distributions. An example is offered by the bimodal distribution of per capita income across Italy’s NUTS2, whose Southern ones are characterized by a lower income level than the ones in the North, and where the two modes represent those two differently developed areas.
The need to find a suitable methodology to handle multimodal distributions and to characterize their dynamics can be satisfied by nonparametric statistical models such as the ones introduced by Quah (1997a; 1997b) as a generalization of Markov transition matrices to the continuum. Firstly, this methodology allows to track distribution dynamics. This overcomes the limits we pointed out above of parametric econometrics as a set of methodologies aiming to synthesize information about a set of statistical units through the quantification of an hypothetically average behaviour. Indeed, Quah’s stochastic kernel allows to emphasize intra-distribution dynamics of subset of units behaving in a rather different way than the average (and likely to be unrepresentative) one of the whole set. While the approach was originally introduced to convergence analysis, we will make a general use of it as a tool for the analysis of polarization dynamics agriculture and of intra-distribution clustering. Secondly, an opportune “version” of stochastic kernel can be used to assess the influence of space as a “conditioning factor”. The rationale is the following. If space “explains” somehow the presence of poles in a distribution, and if we “condition” the latter to spatial information, we will obtain a new distribution which does not present multimodality anymore. On the whole, the methodology appears to be an useful tool in order to analyse both distribution polarization and “polarization of space” of agricultural system.
In particular, our empirical analysis is aimed to stress the main EU agriculture traits about productive structure, productivity and rural development. Our use of stochastic kernel makes this work to be a study of aggregate characteristics of the whole EU territory, rather than a descriptive analysis of a single region or groups of regions. The structure of the paper is the following. The second section describes methodology; section 3 describes the choice of indicators, dataset and presents results, while section 4 concludes.

2. Methodology: the stochastic kernel

2.1 Stochastic kernel and distributions

The view offered by cartograms of selected indicators in figures 1a, 1b, 2a, 2b, 3a, 3b, 4a, 4b, 5a, 5b reports heterogeneous territorial distributions across NUTS 2 in 1980 and 2005, that is at the maximum and minimum of the time interval we consider in our study (see below for a discussion about choice of indicators). Although these graphic representations can express the “initial” and “final” states of a phenomenon diffusion in a territory, the rest of dynamics within these two years can be only deduced, unless an inspection of cartograms in all the years is done. Therefore a complete description of indicators dynamics should refer to all information available over the full interval, and an opportune synthesis of temporal information is requested. From this point of view, statistics offers a wide range of possibilities in order to present an opportune synthesis

of space-time information. Nevertheless, as we remarked above due to their own nature certain "classical" econometric parametric estimates tend to infer a "representative" behaviour from an original set. Whenever units show clustered behaviour, such an estimate would not be able to detect it. Methodologies like univariate kernel density estimates can solve the problem of assessing local behaviours within a distribution. Of course, a time analysis of univariate distributions would just report the same information of a cartogram in a different way, and it would present the same difficulties of synthesizing the basic time features, jointly with the one of highlighting those intra-distribution dynamics determining the evolution of a distribution.
Nonparametric statistical technique of stochastic kernel can help us to solve the methodological remarks we stated. In this sense, useful indications and an opportune econometric framework are offered by Quah's (1997a; 1997b) analysis about convergence and polarization of economies. The latter is a concept dealing with the attitude of statistical units to concentrate in heterogeneous and somehow "distant" clusters, whose members present a certain degree of "similarity" (Esteban and Ray, 1994; Quah, 1997a; Duclos *et al*, 2004). Given a "characteristic", such as income, polarization appears when a portion of a population collects in sub-groups (or "poles"), and thus when the distribution of indicator proxying that characteristic presents multimodality.
Quah introduces a mathematical instrument which allows to track distribution dynamics over time. He employs the continuous version of a transition probability matrix, namely stochastic kernel, whose input is a distribution, rather than a vector or a scalar, and whose output is a three dimensional graph plotting the evolution of a distribution between two generic points of time of a given interval, say t and $t+k$, by using all available time information. The final outcome is an assessment of the underlying law of motion, which puts in evidence the presence and the dynamics of poles.
The operator will allow us to reveal distributions features in the twofold way we mentioned above, as done in Quah (1997a, 1997b). Firstly, the methodology will be used in order to detect whether units tend to similar behaviours, or on the contrary if data indicate an overtaking in relative positions, and in any case if a clustered behaviour appears. Secondly, we will use Quah's generalization of stochastic kernel to a broader scheme which aims to detect the influence of a "conditioning factor" on a distribution, following a regression-like rationale. Under the latter point of view, changes in distribution's shape induced by the conditioning factor can be indicative of its influence over units' relative position, thus overcoming the limits of parametric techniques we pointed out above. This extension of stochastic kernel to the assessment of relationship between variables can allow to point out those global patterns or local behaviours of a distribution which are conditioned by a "factor" such as a variable or a spatial contiguity matrix.

2.2 Methodology of stochastic kernel

A technical derivation of stochastic kernel is presented by Quah (1997b, 2000). Let F_t be a distribution, say, of incomes at time t, which is the realization of a random element from a space of income distributions. We indicate with λ_t in $(\mathbf{B},\mathfrak{B})$ a measure associated with F_t, where $(\mathbf{B},\mathfrak{B})$ is a measurable space defined as follows. Let $\mathbb{R}$ be the real line, and $\mathfrak{R}$ the collection of its Borel sets: we denote with $\mathbf{B}(\mathbb{R},\mathfrak{R})$ the Banach space of bounded finitely-additive set functions on $(\mathbb{R},\mathfrak{R})$ endowed with total variation norm $\forall\mu$ in $\mathbf{B}(\mathbb{R},\mathfrak{R})$: $|\mu| = \sup\sum_j |\mu(A_j)|$, where $\{A_j : i = 1,2,...,n\}$ are finite measurable partitions of $\mathbb{R}$. Empirical distributions on $\mathbb{R}$ can be identified with probability measures on $(\mathbb{R},\mathfrak{R})$, which are countably-additive elements in $\mathbf{B}(\mathbb{R},\mathfrak{R})$ assigning value 1 to the entire space $\mathbb{R}$. $\mathfrak{B}$ is the Borel σ-algebra generated by the open subsets (relative to total variation norm topology) of $\mathbf{B}(\mathbb{R},\mathfrak{R})$.

If we indicate with $(\Omega,\mathfrak{F},\Pr)$ the probability space underlying λ_t, the latter is the value of an $\mathfrak{F}/\mathfrak{B}$-measurable map $\Lambda_t : (\Omega,\mathfrak{F}) \to (\mathbf{B},\mathfrak{B})$. The sequence $\{\Lambda_t : t\}$ is a **B**-valued stochastic process as *t* evolves.

To understand how the law of motion is modelled, we express the relationship between two measures of two distributions at different times, λ_t and λ_{t-1}, though a stochastic difference equation, which is analogous to a first-order autoregression model:

$$\lambda_t = T^*(\lambda_{t-1}, u_t) = T^*_{u_t}(\lambda_{t-1}), t \geq 1. \tag{1}$$

In the equation T^* is an operator mapping λ_{t-1} together with disturbances u into λ_t, while $T^*_{u_t}$ absorbs the disturbances into the operator itself.

Given two elements of **B**, say μ and ν, that are probability measures on $(\mathbb{R},\mathfrak{R})$, stochastic kernel relating these elements is a mapping $M_{(\mu,\nu)} : (\mathbb{R},\mathfrak{R}) \to [0,1]$. Given an income level *y*, the features of *M* allow it to be "a complete description of transitions from state *y* to any other portion of the underlying state space $\mathbb{R}$" (Quah, 2000, p.77).

What is the relationship between *M* and T^* in (1)? The stochastic kernel simply "represents" T^*, and therefore maps λ_{t-1} into λ_t, tracking where F_t points in F_{t-1} end up, then encoding information on intra-distribution dynamics. The detailed mathematical procedure which relates the two operators can be found in Quah (1997b, 2000); here we resume it by reporting a statement of Quah concerning the role of : "[…] stochastic kernel *M* representing T^*[, which] can be used to relate any two different distributions, in particular an unconditional observed distribution, and one conditional on a set of explanatory factors".

2.3 Interpreting stochastic kernel output: distribution dynamics

As mentioned above, the outcome of stochastic kernel estimate[3] is a three dimensional plot. When this methodology is employed to assess the law of motion of a distribution evolving over time, shape and position of the probability mass are indicative of distribution and clubs dynamics between two periods *t* and *t+k*. The output reports times *t* and *t+k* in the horizontal axes, while density is in the vertical one.

Contour plot can be very helpful in order to interpret these three dimensional graphics. Since in the present work we employ conditioned to the sectional mean distributions, as indicated by Quah, our explanation of stochastic kernel interpretation will refer to this specific case. When probability mass lays on the 45 degrees diagonal of X-Y axis, this

[3] For details about estimation procedures, see Quah (1997a, paragraph 4).

indicates that distribution remained unchanged over time. When the mass, or a part of it, lays parallel to the *t* axis, and concentrates around the value 1 of *t+k* axis, there appears to be a phenomenon of convergence towards the mean; more in general, a situation of the mass laying parallely to the *t* axis would indicate a situation of polarization, since units being in a wider range of values in *t* become more concentrated between each other in *t+k*. An opposite situation would be when the mass lays parallely to the *t+k* axis: this would indicate a situation of divergence.

2.4 Stochastic kernel in a regression-like rationale

This section presents a description of the use of stochastic kernel in a regression model-like rationale, as in Quah (1997a, 1997b), where it maps the evolution from the original to a conditioned distribution. The generic procedure which allows to obtain the conditioned distribution from the original one, say *Y*, is called "conditioning scheme", and it is indicated by *G*. Let $Y_l(t)$ be the value assumed by *Y* in economy *l* at time *t* ($l \in C \subseteq I$, where *I* is the whole set of considered economies and *C* is a subset of *I*); let $\tilde{Y}_l(t)$ be the "conditioned version" of $Y_l(t)$. *G* is then the collection of the triple $\tau_l(t)$, $C_l(t)$ and $\varpi_l(t)$, where $\tau_l(t)$ indicates the lag with which developments in economies $C_l(t)$ affect $Y_l(t)$, as mediated through weights $\varpi_l(t)$; $C_l(t)$ is the collection of economies associated with *l* in *t*; $\varpi_l(t)$ is a set of probability weights never positive outside $C_l(t)$. Defined $\hat{Y}_l(t) \stackrel{\text{def}}{=} \sum_{j \text{ in } C_l(t)} \varpi_j(t) Y_j(t - \tau_l(t))$, conditioned distribution of *Y* is given by

$$\tilde{Y}_l(t) \stackrel{def}{=} \phi\left(Y_l(t), \hat{Y}_l(t)\right)^4. \tag{2}$$

where $\phi : \mathbb{R}^2 \to \mathbb{R}$; following Quah (1997a), in this paper we consider ϕ as the ratio.
As pointed out in the last section, contour plots can be helpful in order to detect changes in probability mass shape. When the factor has no influence on the considered variable, probability mass lays on the 45 degrees diagonal of X-Y axis, which report respectively original and conditioned distribution. A "more or less" parallel mass to the "original" axis indicates a "more or less" relevant influence of the factor over the original variable. This latter method will be used in the present work in order to study the influence of spatial contiguity of NUTS 2 over distributions.

3. Dataset and results

3.1 Choice of indicators and dataset

Our analysis of peculiarities and discontinuities across NUTS 2 agriculture focuses on productive structure, productivity and rural development. The choice of these topics, as

[4] For further details see Quah (1997b, *Technical appendix*).

well as the one of their proxies, was driven by five stylized facts[5] concerning EU agriculture.

1. The declining of the primary sector, supported by the significant productivity gains of labour and capital and the sharp decline in relative prices.
2. Primary sector still plays a major role in some regions.
3. Agriculture still occupies a relevant part of EU territory.
4. There appears to be an average annual decrease in employment.
5. Productivity gains largely supported by technological process, as well as the overall economic pressures, have driven a considerable structural adjustment over the last decades.

Our overlook on productive structure considers three indicators: the number of employed in agriculture, the percentage of employed in agriculture over the total number of employed, and the ratio between agriculture GVA and total GVA. Indicator of productivity is GVA per worker. Rural development is proxied by GVA - density of inhabitants per square kilometre ratio, the latter computed as ratio between population and surface in square kilometre.
Sources of our dataset are Cambridge Econometrics (2005) and Eurostat (2007). Specifically, indicators from Cambridge Econometrics are *GVA in 1995 Euros*, *Employment* and *Population*. Surface in square kilometres is taken from Eurostat.
The sample is made of 194 NUTS 2 belonging to EU-15, whose composition is reported in Appendix A. The choice of a smaller sample than the whole one of NUTS 2 was driven by the necessity to obtain the biggest sample over the longest time period (1980-2005).

3.2 Results

Results of our analysis are shown in Appendix B. We report cartography in 1980 and 2005 of each indicator (figures .a and figures .b), as well as the time plot of mean value evolution (figures .c), in order to give an earlier descriptive overview about both territorial and average time evolution. Classes of cartograms are determined by computing each *i*th quartile in 1980 and 2005 – respectively Q_{80}^{i} and Q_{05}^{i} – on each distribution F_{80} and F_{05}. Interval of the first class is $\left(\min\left(\min\left(F_{80}\right);\min\left(F_{05}\right)\right);Q_{80}^{1}\right)$; for each *j*th class the interval is $\left(Q_{80}^{j-1};Q_{80}^{j}\right)$, except for the last one, where it is $\left(Q_{80}^{j-1};\max\left(Q_{80}^{j};Q_{05}^{j}\right)\right)$.
All kernel densities, both univariate and stochastic, concern distributions standardised to each year's sectional mean[6]. Boxplots (figures .d) and densities were estimated[7] (figures .e) for selected years (1980, 1988, 1997, 2005) in order to give an initial idea of univariate distributions features and shape. For each indicator two stochastic kernel estimates were performed. The first one (figures .f) presents distribution dynamics from *t* to *t*+5[8]. The second one (figures .g) assesses the role of spatial factor in altering

[5] See European Commission (2007), pp.10-21.
[6] See Quah (1997a, 1997b, 2000).
[7] Kernel density estimator is defined by $\hat{f}\left(x\right)=\left(1/nh\right)\sum_{i=1}^{n}K\left[\left(x-X_{i}\right)/h\right]$, where *h* is called *smoothing parameter* or *bandwidth*, and *K* is the kernel function. In our univariate estimates *h* is chosen according to Silverman criterion (see Quah, 1997), and *K* is a Gaussian kernel.
[8] See Quah (1997a).

distributions by tracking the evolution from the original distribution to the one conditioned on physical neighbours[9].

Employed in agriculture

Both the view of cartograms of employed in agriculture brightening up from 1980 (figure 1.a) to 2005 (figure 1.b), and the decreasing trend of the series reported in figure 1.c, confirm the well-known tendency of employment in agriculture to decrease. Boxplots report a slight reduction of variability (figure 1.d) and of outliers, while univariate distribution appears to progressively form a pole around a value of about 2.5 (figure 1.e). Distribution dynamics (figure 1.f) points out a substantial invariance of territories' relative position over the time interval.
The space factor seems to reveal two distinct behaviours. A first group is made by territories in a low, middle and middle-high relative position which are strongly influenced by it. Instead countries in the highest rankings do not seem to be affected by contiguity in such an evident way.
On the whole, while the average number of employed in agriculture decreases, and this phenomenon is widespread, the reduction affects all territories for they globally maintain the same relative positions, although this behaviour seems to vary. Thus, in terms of number of employed agriculture across NUTS appears to reduce its dimensions and concentrate in space.

Employed in agriculture / total employed ratio

Decreasing trend of occupational levels in agriculture at NUTS 2 level is reaffirmed by a measure of structural composition of employment such as the share of employed in agriculture over the total of all sectors. The increasing number of outliers in figure 2.d suggests that variability of employment structure rose. We also note a slight growing polarization from 1980 to 2005 in figure 2.e, which seems to affect countries with a higher relative position; nevertheless stochastic kernel (figure 2.f) reveals that 5 years time span dynamics substantially leaves territories relative position unchanged. For what concerns the influence of the space factor, figure 2.g suggests that contiguity crucially explains the indicator, except for a small group which persists on the main diagonal. Globally, this seems to indicate that similar productive structures in agriculture appear to be spatially contiguous, except for the small group in a middle-high relative position.

Agriculture GVA / total GVA ratio

In line with trends in employment, a progressive decreasing incidence of agricultural GVA on the total one can be noted (figures 3.a, 3.b, 3.c). Intra-distribution dynamics presents an increase of the median values of distributions (figure 3.d) where polarization tends to diminish (figure 3.e). This evidence is confirmed by distribution dynamics (figure 3.f), which indicates a reduction of polarization from high relative positions to lower ones. Figure 3.g confirms the relevance of spatial contiguity as factor explaining original distribution, and a negligible small number of units persististing in the main diagonal.

[9] See `ddCndScheme` procedure in Quah (2000), p.74-83.

Results globally confirm the decreasing importance of agriculture for modern economies, as well as the relevance of the space factor for the indicator, although for some regions primary sector still contributes to global GVA production in a relevant way. As noticed about *Employed in agriculture / total employed ratio*, territories with a similar structural composition appear to be spatially contiguous also here.

GVA per employed

Despite the reduction of employment in agriculture we already observed, GVA per employed analysis reveals interesting aspects. A comparison between figures 4.a and 4.b, as well as the trend reported in figure 4.c, put in evidence the heavy increase of agriculture productivity, which is combined with a substantial invariance of unimodality of distributions (figure 4.d and 4.e). Distribution dynamics reveals a clear reduction of higher relative positions (figure 4.f), which would indicate that the overall growth of productivity has mostly involved regions with lower relative positions. Spatial factor (figure 4.g) appears to influence distributions especially in the middle part of probability mass.

Since this productivity indicator allows to evaluate the impact of EU agricultural policies, a more detailed analysis would be needed in order to fully explain the peculiar time behaviour, which doesn't fall within the scopes of this paper to describe the global behaviour of NUTS 2. From what emerges here we just consider that while EU policies sustained incomes with no regard for mostly and naturally productive divisions, they allowed an integration of economic systems in some way.

A further analysis conditions GVA to the number of employed (figure 4.h). As expected, the latter factor has a strong influence on agriculture. Low-medium part of original distribution is totally explained by the considered conditioning factor, while in the higher part of the distribution we observe a sort of bifurcation. This might be associated to different incidence of employment on regions with similar relative high positions. Thus this kind of "Y" shape, indicating the presence of two clusters of territories where the relationship appears to be "somewhat different", might lead to think about different productive models, where technology might have a non uniform role. This evidence also confirms the utility of our nonparametric approach, which highlights distributional features that a parametric approach may treat as "distortions" or "errors" from the average behaviour, and in any case as something which would not be estimated.

GVA/density ratio

As we pointed out above, NUTS 2 level can not be an adequate territorial grid especially for evaluations about rurality[10]. Nevertheless this proxy reveals an increasing trend in levels between 1980 and 2005. Distributions are characterised by a slight decreasing variability of the third quartile, while many outliers appear (figure 5.d). Univariate densities present many bumps, besides the highest peak which correspond to a very close to zero value. Distribution dynamics (figure 5.f) reveals a progressive convergence of NUTS characterized by a middle-high relative position, while as expected figure 5.g indicates that the indicator is heavily conditioned by contagion effect.

[10] See European Commission (2007), Annex 3.

4. Conclusions

Despite the limit due to data availability, which conditions the possibility to extend results to a wider context and to take into account a more detailed territorial grid such as NUTS 3, results confirm two important research hypotheses. The former concerns the necessity to investigate economic and social phenomena though methodologies which can be able to catch heterogeneities linked to spatial discontinuity. The latter is linked to the importance of modelling territorial effects though spatial constraints. Our effort is to combine these two aspects in analysing a sector which is strongly linked to features of territories.

The joint interpretation of indicators describes the quantitative reduction of agricultural structure as a process presenting a strong territorial differentiation. Primary sector still remains an important element for many regional economies, which is expressed by the relevance of investments of CAP. Performance of productivity indicator suggests the existence of different degrees of technological innovation at regional level. This clearly influences competitiveness of NUTS 2 agricultures, and should be supported by policies which would be able to sustain investments of private sector. This matches with the trend of regions in middle-high relative positions to change their ranking in almost all the analysis we performed. Proxy of rurality is strongly conditioned to spatial contiguity as expected, although territorial level of NUTS 2 does not allow to emphasize urban and rural dynamics in the most proper way.

References

Duclos, J. Y., Esteban, J. M. and Ray, D. (2004), *Polarization: Concepts, Measurement and Estimation,* Econometrica, 72: 1737-1772

Esteban, J. M. and Ray, D. (1994), *On the Measurement of Polarization*, Econometrica, 62: 819-851

European Commission (2007), *Situation and perspective for EU agriculture and rural areas,* http://ec.europa.eu/

Henderson, J. V. (1988), *Urban Development. Theory, Fact and Illusion*. New York: Oxford University Press

Léon, Y. (2005), *Rural development in Europe: a research frontier for agricultural economists*, European Review of Agricultural Economics, 32: 301-317

Notarstefano G. and Scuderi R. (2007), *Agricultural and rural development: a study about polarization and distribution dynamics*, Proceedings of the 47th ERSA Congress

Quah D. T. (1997a), *Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs*, Journal of Economic Growth, 2: 27-59

Quah D.T. (1997b), Regional *cohesion from local isolated actions: II. Conditioning*, Centre for Economic Performance Discussion Paper no. 379, December.

Quah D.T. (2000), *The TSRF Reference Manual*, http://econ.lse.ac.uk/~dquah/

Wolfson M. C. (1994), *When Inequalities Diverge*, The American Economic Review, Papers and Proceedings of the Hundred and Sixth Annual Meeting of the American Economic Association, 84: 353-358.

Appendix A – NUTS 2 sample composition

AT11	Burgenland
AT12	Niederösterreich
AT13	Wien
AT21	Kõrnten
AT22	Steiermark
AT31	Oberösterreich
AT32	Salzburg
AT33	Tirol
AT34	Vorarlberg
BE10	Bruxelles-Brussels
BE21	Antwerpen
BE22	Limburg
BE23	Oost-Vlaanderen
BE24	Vlaams Brabant
BE25	West-Vlaanderen
BE31	Brabant Wallon
BE32	Hainaut
BE33	Liège
BE34	Luxembourg
BE35	Namur
DE11	Stuttgart
DE12	Karlsruhe
DE13	Freiburg
DE14	Tübingen
DE21	Oberbayern
DE22	Niederbayern
DE23	Oberpfalz
DE24	Oberfranken
DE25	Mittelfranken
DE26	Unterfranken
DE27	Schwaben
DE50	Bremen
DE60	Hamburg
DE71	Darmstadt
DE72	Gießen
DE73	Kassel
DE91	Braunschweig
DE92	Hannover
DE93	Lüneburg
DE94	Weser-Ems
DEA1	Düsseldorf
DEA2	Köln
DEA3	Münster
DEA4	Detmold
DEA5	Arnsberg
DEB1	Koblenz
DEB2	Trier
DEB3	Rheinhessen-Pfalz
DEC0	Saarland
DEF0	Schleswig-Holstein
DK	Danmark
ES11	Galicia
ES12	Principado de Asturias
ES13	Cantabria
ES21	Pais Vasco
ES22	Comunidad Foral de Navarra
ES23	La Rioja
ES24	Aragón
ES30	Comunidad de Madrid
ES41	Castilla y León
ES42	Castilla-La Mancha
ES43	Extremadura
ES51	Cataluña
ES52	Comunidad Valenciana
ES53	Illes Balears
ES61	Andalucia
ES62	Región de Murcia
ES63	Ceuta
ES64	Melilla
ES70	Canarias
FI13	Itä-Suomi
FI18	Etelä-Suomi
FI19	Länsi-Suomi
FI1A	Pohjois-Suomi
FI20	Åland
FR10	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre
FR25	Basse-Normandie
FR26	Bourgogne
FR30	Nord - Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-ComtÚ
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-PyrÚnÚes
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Prov.-Alpes-Côte d'Azur
FR83	Corse
GR11	Anatoliki Makedonia, Thraki
GR12	Kentriki Makedonia
GR13	Dytiki Makedonia
GR14	Thessalia
GR21	Ipeiros
GR22	Ionia Nisia
GR23	Dytiki Ellada
GR24	Sterea Ellada
GR25	Peloponnisos
GR30	Attiki
GR41	Voreio Aigaio
GR42	Notio Aigaio
GR43	Kriti
IE01	Border, Midland and Western
IE02	Southern and Eastern
ITC1	Piemonte
ITC2	Valle d'Aosta/VallÚe d'Aoste
ITC3	Liguria
ITC4	Lombardia
ITD1	Provincia Autonoma Bolzano/Bozen
ITD2	Provincia Autonoma Trento
ITD3	Veneto
ITD4	Friuli-Venezia Giulia
ITD5	Emilia-Romagna
ITE1	Toscana
ITE2	Umbria
ITE3	Marche
ITE4	Lazio
ITF1	Abruzzo
ITF2	Molise
ITF3	Campania
ITF4	Puglia
ITF5	Basilicata
ITF6	Calabria
ITG1	Sicilia
ITG2	Sardegna
NL11	Groningen
NL12	Friesland
NL13	Drenthe
NL21	Overijssel
NL22	Gelderland
NL31	Utrecht
NL32	Noord-Holland
NL33	Zuid-Holland
NL34	Zeeland
NL41	Noord-Brabant
NL42	Limburg (NL)
PT11	Norte
PT15	Algarve
PT16	Centro (P)
PT17	Lisboa
PT18	Alentejo
SE01	Stockholm

SE02	Östra Mellansverige
SE04	Sydsverige
SE06	Norra Mellansverige
SE07	Mellersta Norrland
SE08	Övre Norrland
SE09	Småland med öarna
SE0A	Võstsverige
UKC1	Tees Valley and Durham
UKC2	Northumberland and Tyne and Wear
UKD1	Cumbria
UKD2	Cheshire
UKD3	Greater Manchester
UKD4	Lancashire
UKD5	Merseyside
UKE1	East Riding and North Lincolnshire
UKE2	North Yorkshire
UKE3	South Yorkshire
UKE4	West Yorkshire
UKF1	Derbyshire and Nottinghamshire
UKF2	Leicestershire, Rutland and Northamptonshire
UKF3	Lincolnshire
UKG1	Herefordshire, Worcestershire and Warwickshire
UKG2	Shropshire and Staffordshire
UKG3	West Midlands
UKH1	East Anglia
UKH2	Bedfordshire and Hertfordshire
UKH3	Essex
UKI1	Inner London
UKI2	Outer London
UKJ1	Berkshire, Buckinghamshire and Oxfordshire
UKJ2	Surrey, East and West Sussex
UKJ3	Hampshire and Isle of Wight
UKJ4	Kent
UKK1	Gloucestershire, Wiltshire and North Somerset
UKK2	Dorset and Somerset
UKK3	Cornwall and Isles of Scilly
UKK4	Devon
UKL1	West Wales and The Valleys
UKL2	East Wales
UKM1	North Eastern Scotland
UKM2	Eastern Scotland
UKM3	South Western Scotland
UKM4	Highlands and Islands
UKN0	Northern Ireland

Appendix B – Figures

Figure 1.a – Employed in agriculture (thousands), territorial distribution, 1980

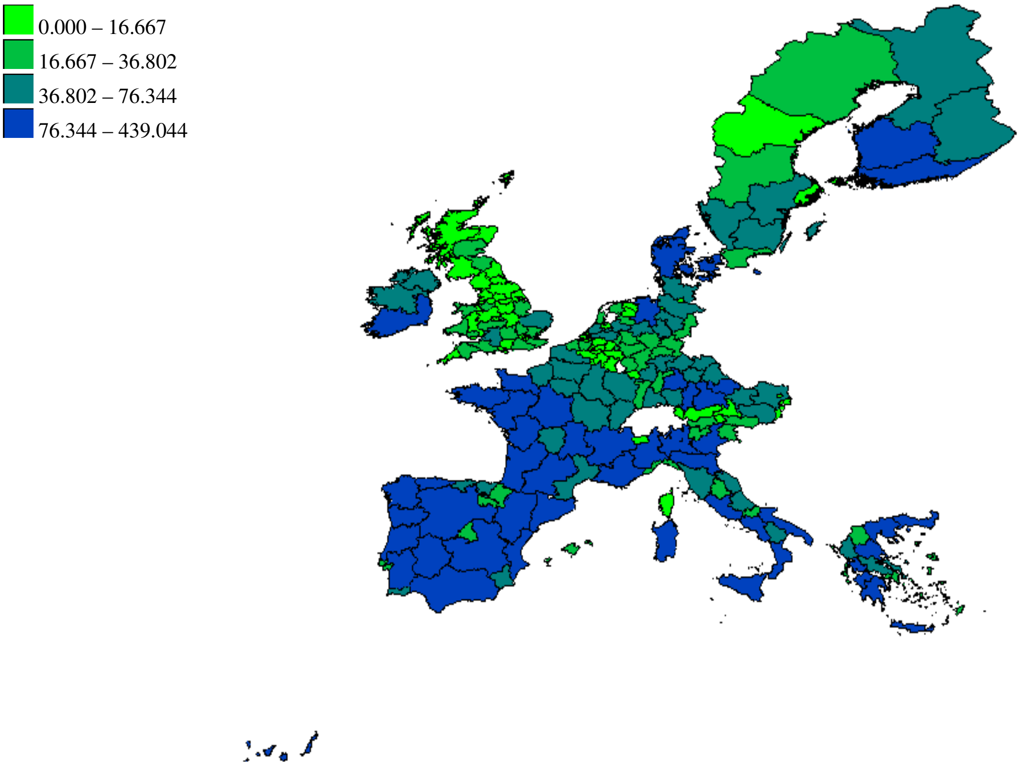


Figure 1.b – Employed in agriculture (thousands), territorial distribution, 2005

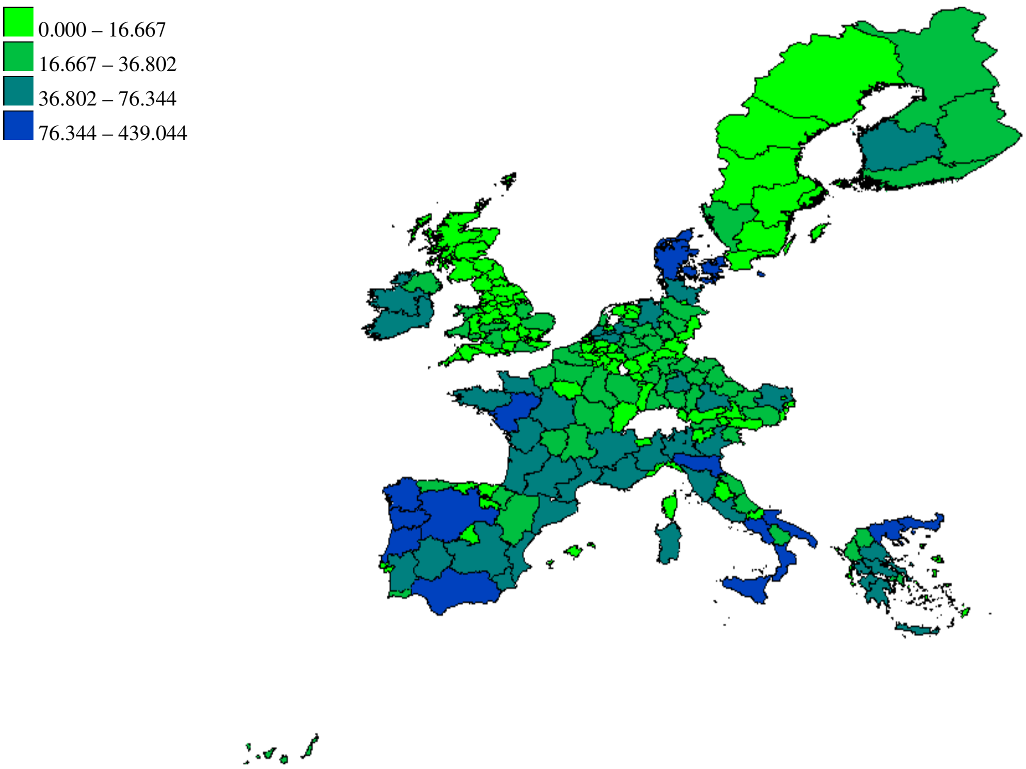


Figure 1.c – Employed in agriculture (thousands), mean values across NUTS 2 sample

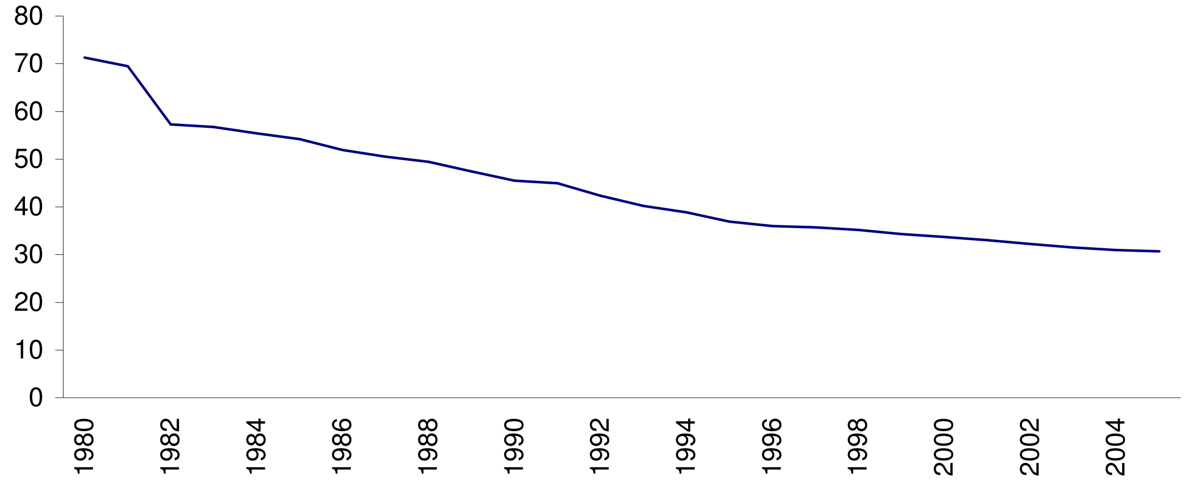
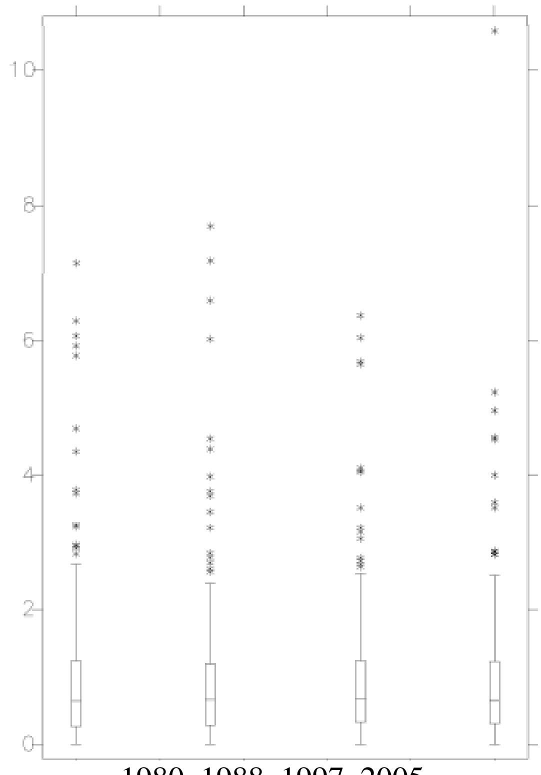
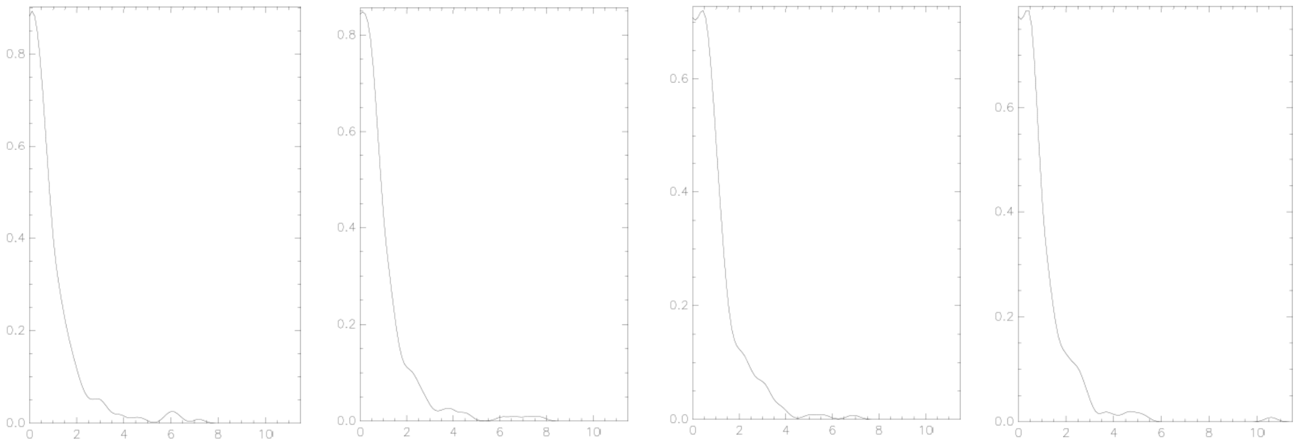


Figure 1.d – Tukey boxplot of relative employed in agriculture



1980, 1988, 1997, 2005

Figure 1.e – Densities of relative employed in agriculture



1980 1988 1997 2005

Figure 1.f – Stochastic kernel: relative employed in agriculture distribution dynamics

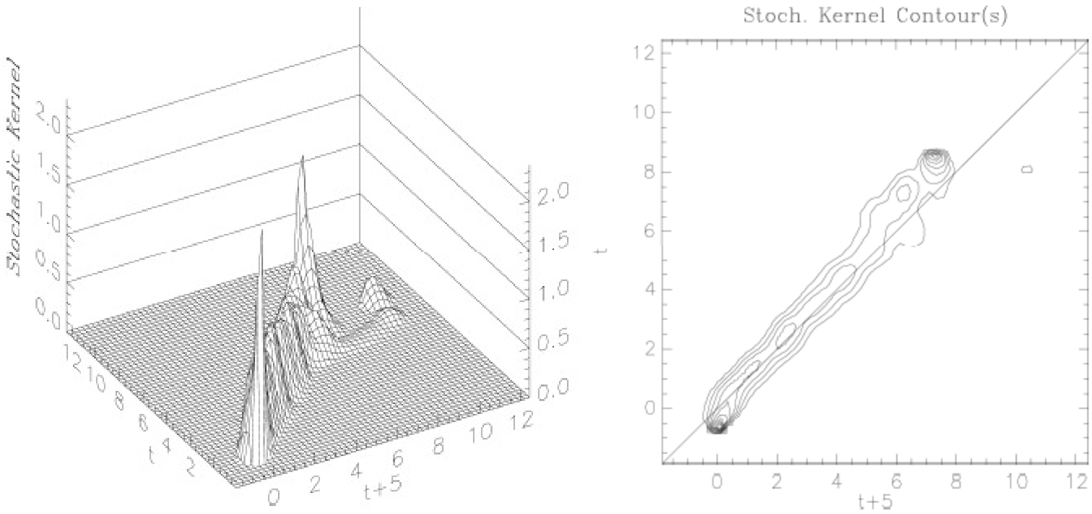


Figure 1.g– Stochastic kernel: relative employed in agriculture distribution conditioned to spatial contiguity

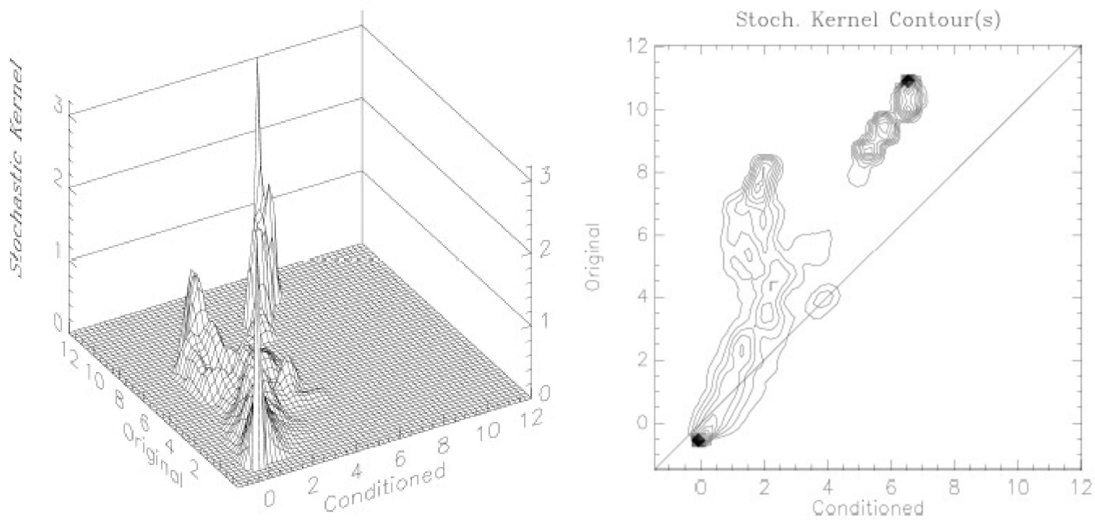


Figure 2.a – Employed in agriculture / total employed ratio, territorial distribution, 1980

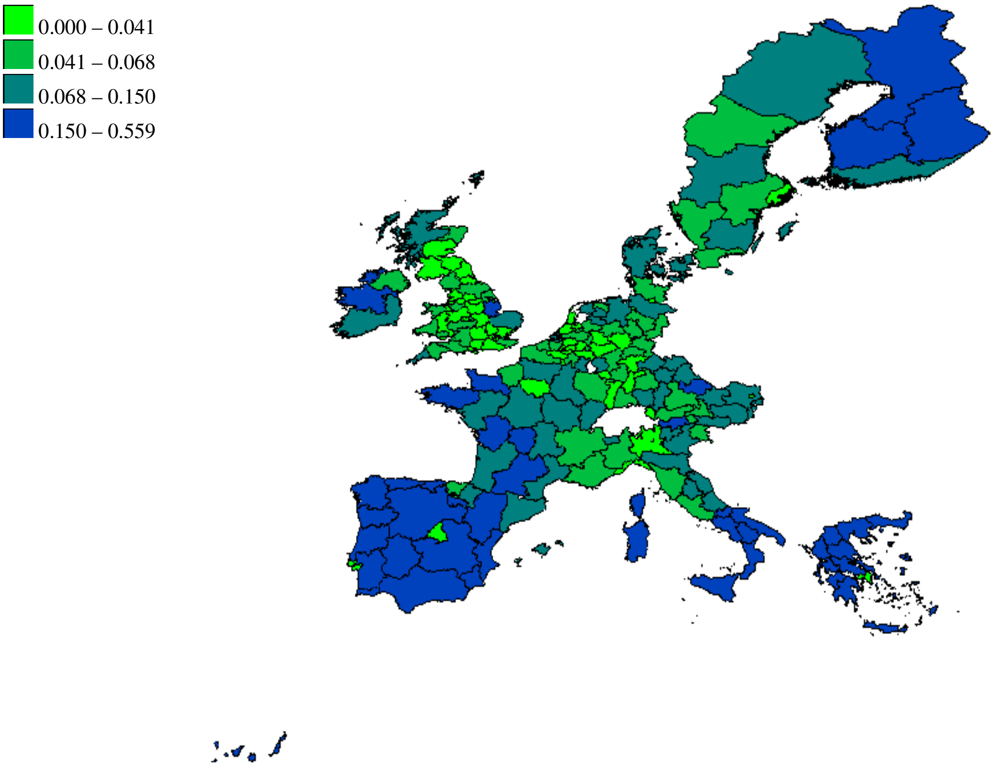


Figure 2.b – Employed in agriculture / total employed ratio, territorial distribution, 2005

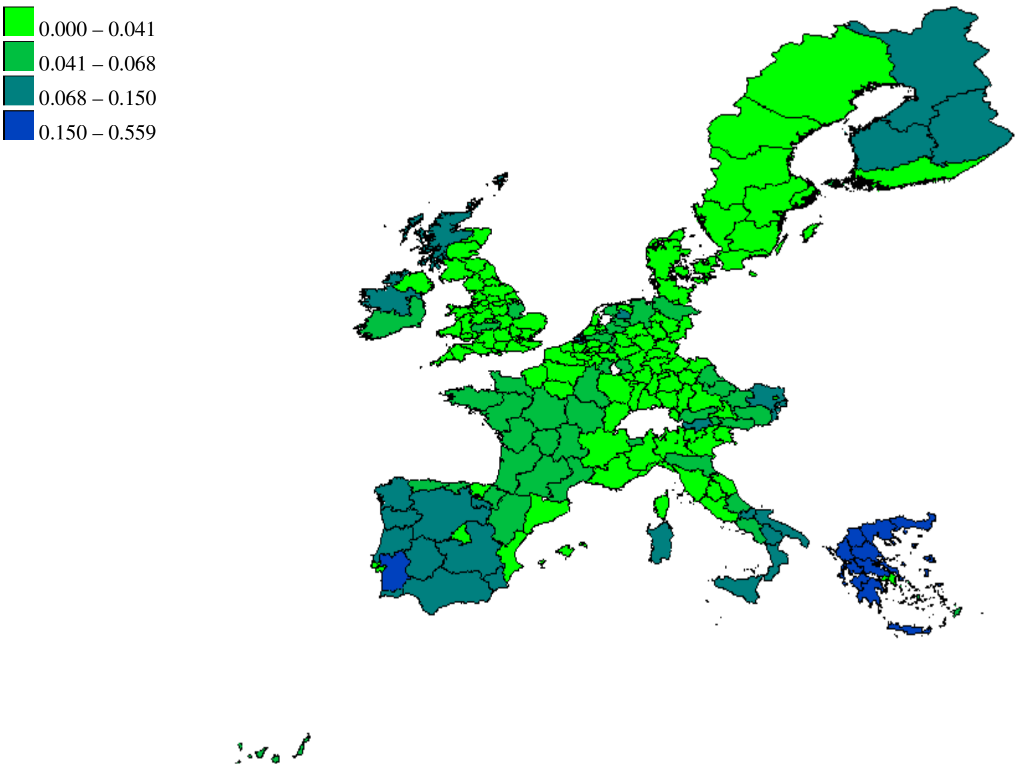


Figure 2.c – Employed in agriculture / total employed ratio, mean values across NUTS 2 sample

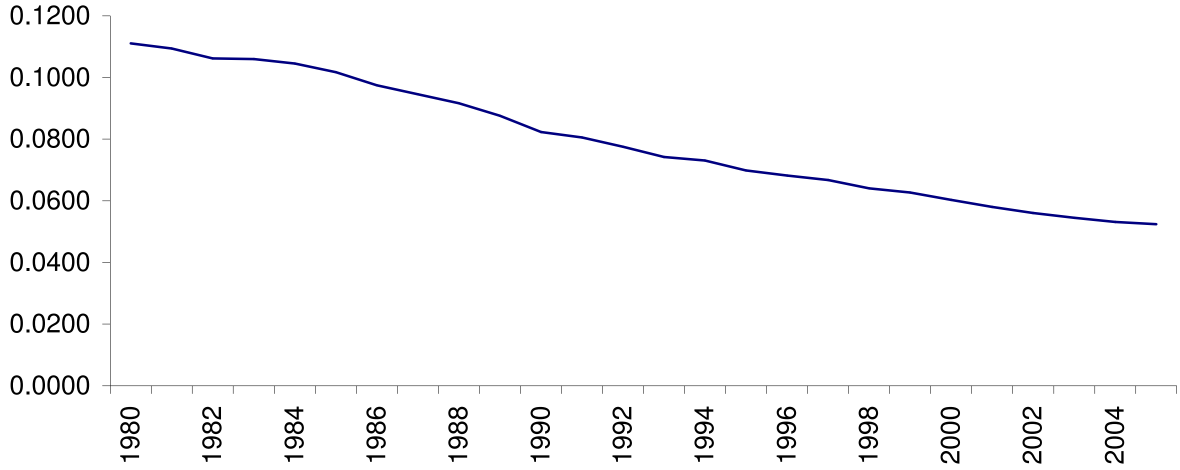
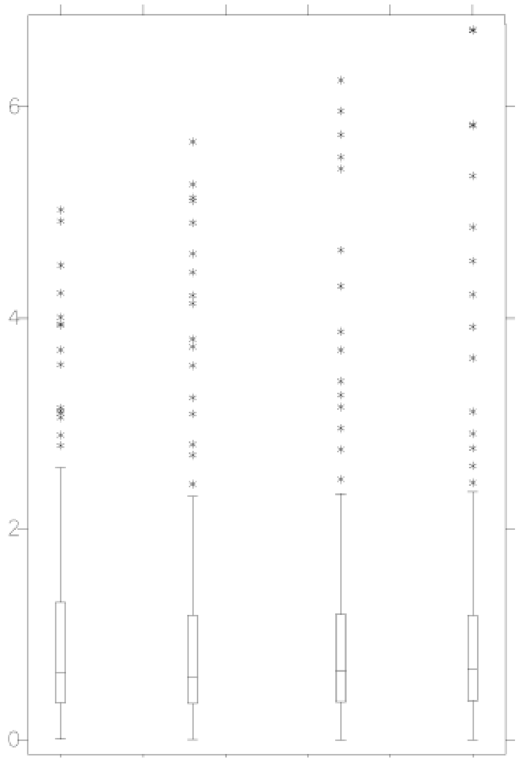
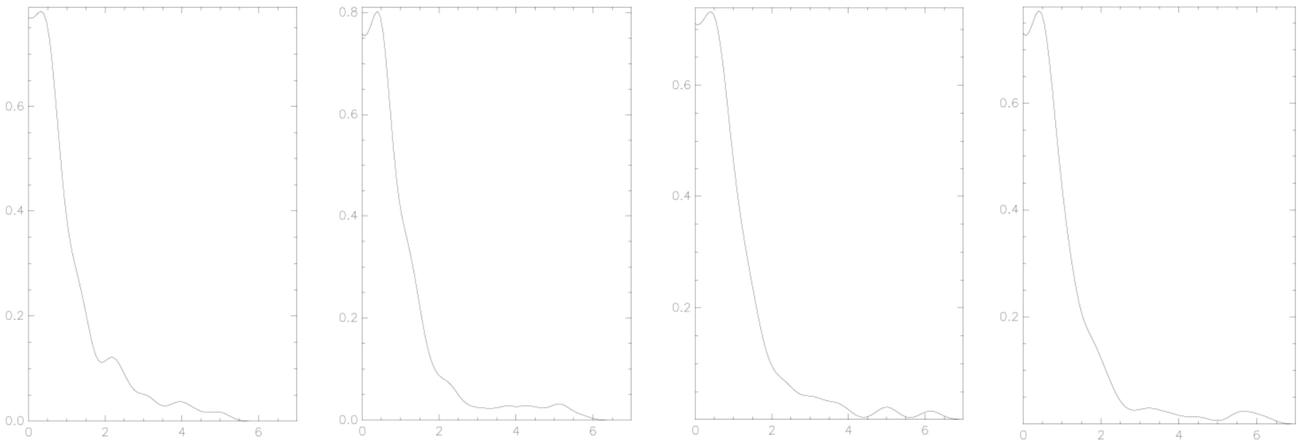


Figure 2.d – Tukey boxplot of relative employed in agriculture / total employed ratio



1980, 1988, 1997, 2005

Figure 2.e – Densities of relative employed in agriculture / total employed ratio



1980 1988 1997 2005

Figure 2.f – Stochastic kernel: employed in agriculture / total employed ratio distribution dynamics

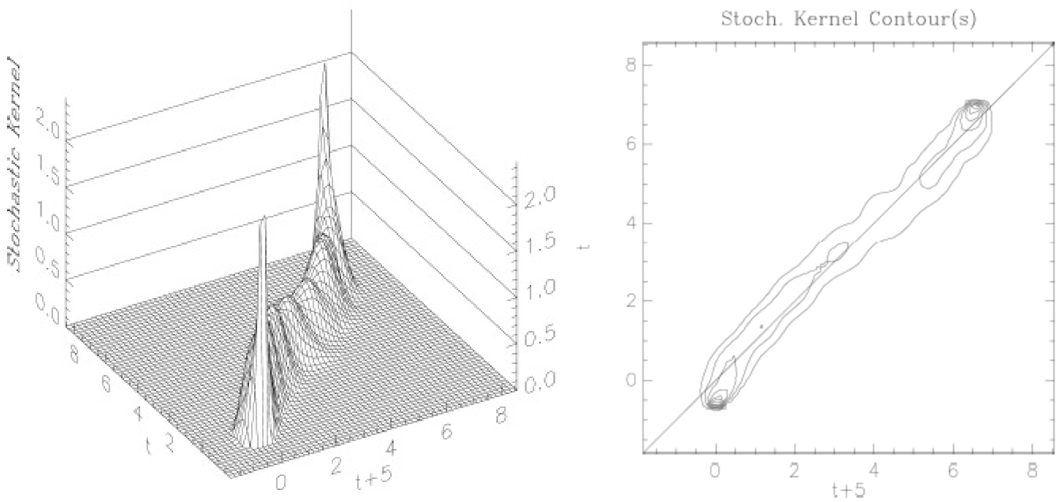


Figure 2.g – Stochastic kernel: relative employed in agriculture / total employed ratio distribution conditioned to spatial contiguity

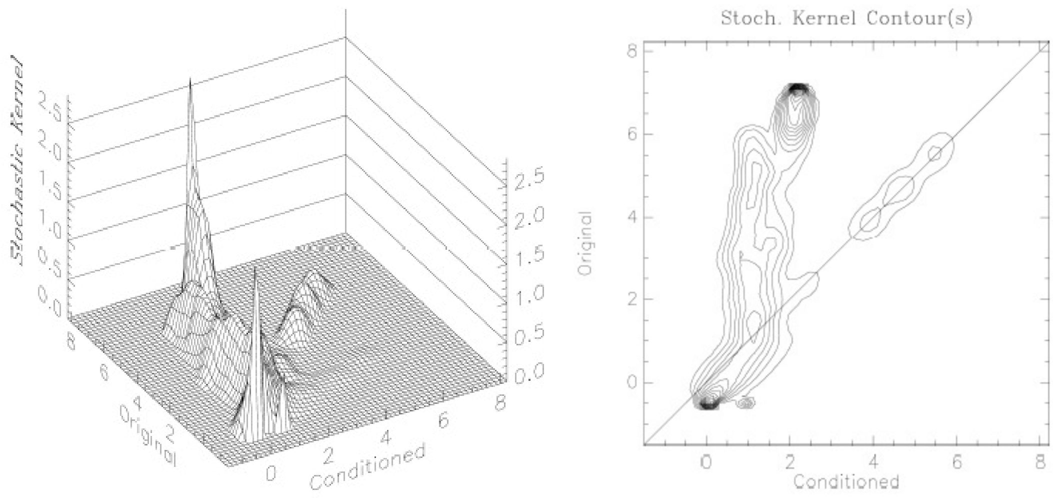


Figure 3.a – Agriculture GVA / total GVA ratio, territorial distribution, 1980

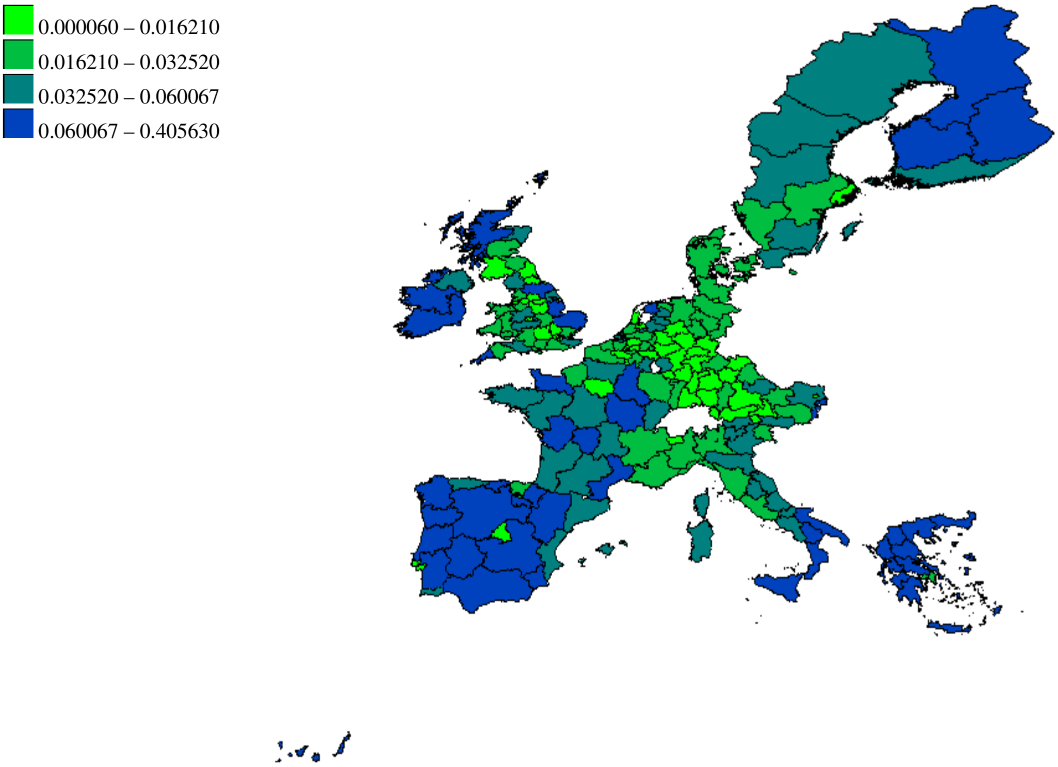


Figure 3.b – Agriculture GVA / total GVA ratio, territorial distribution, 2005

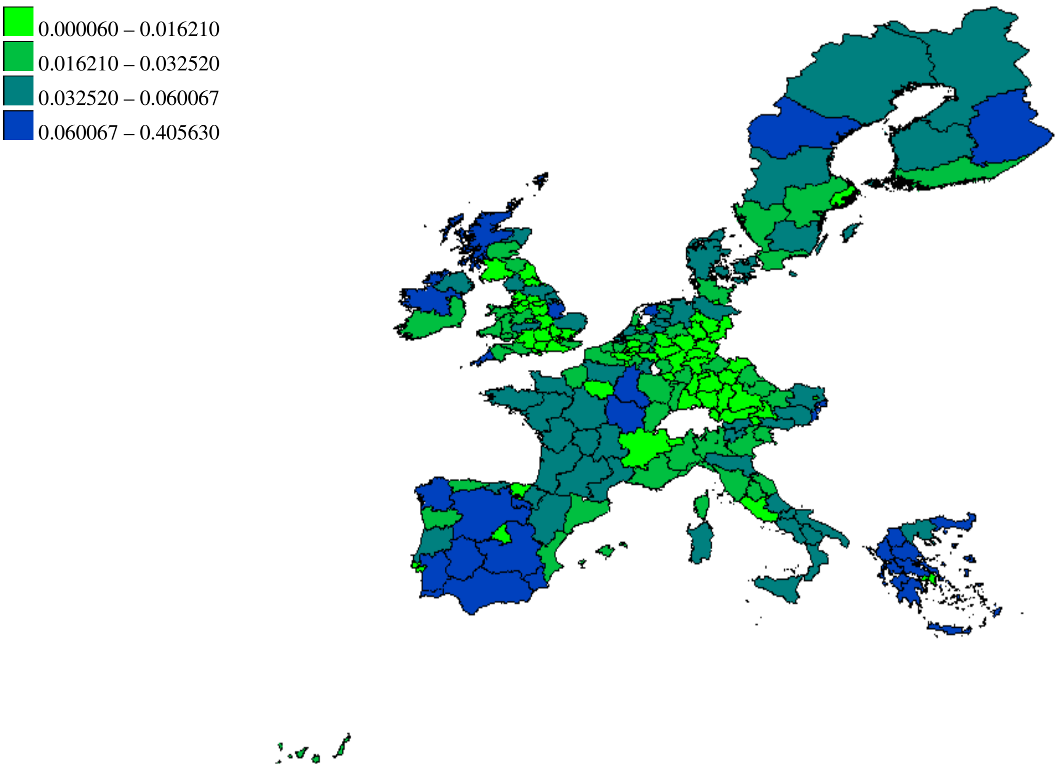


Figure 3.c – Agriculture GVA / total GVA ratio, mean values across NUTS 2 sample

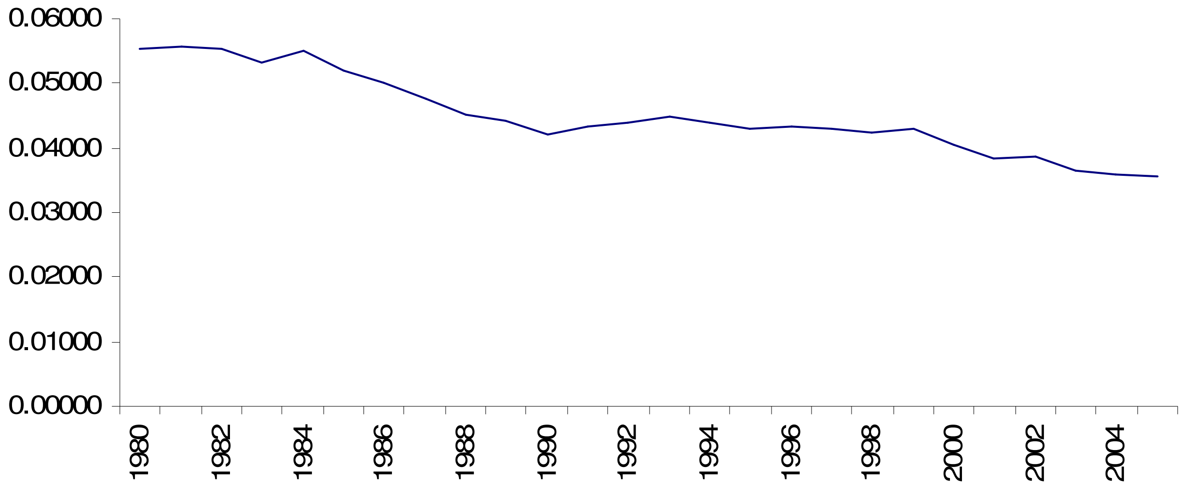
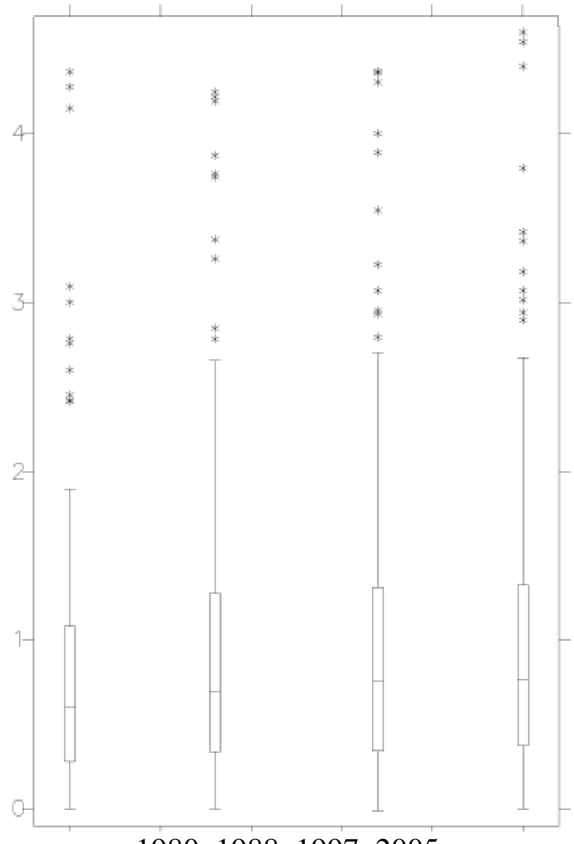
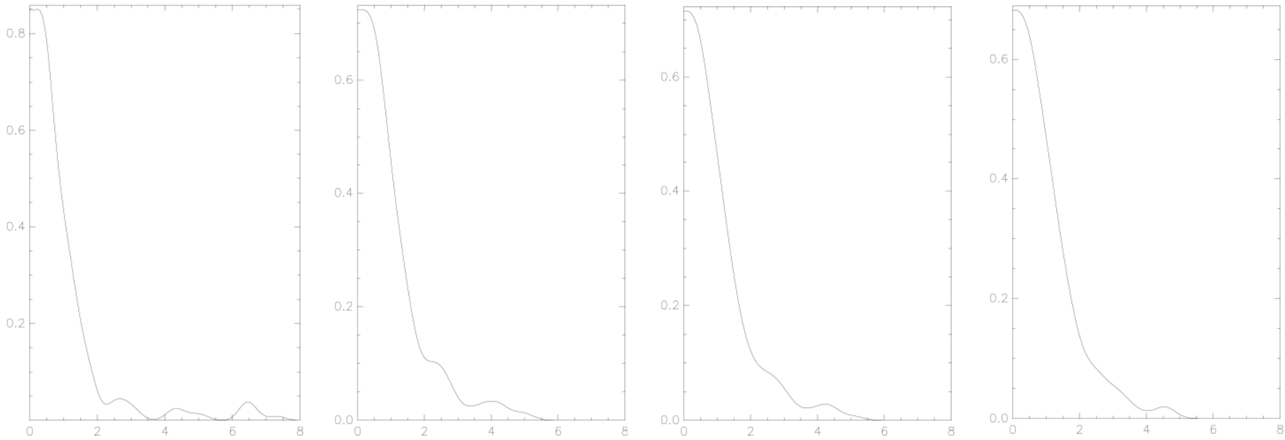


Figure 3.d – Tukey boxplot of relative agriculture GVA / total GVA ratio



1980, 1988, 1997, 2005

Figure 3.e – Densities of relative agriculture GVA / total GVA ratio



1980 1988 1997 2005

Figure 3.f – Stochastic kernel: relative agriculture GVA / total GVA ratio distribution dynamics

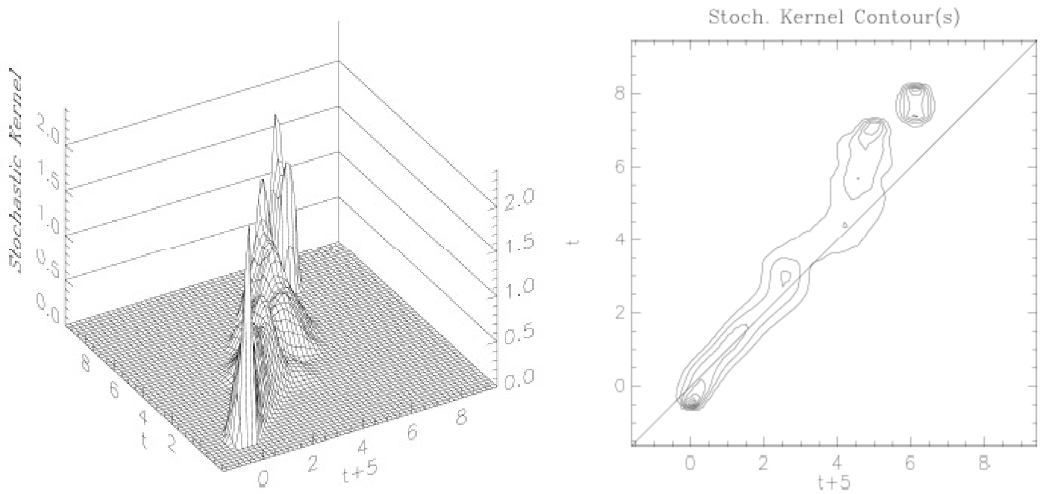


Figure 3.g – Stochastic kernel: relative agriculture GVA / total GVA ratio distribution conditioned to spatial contiguity

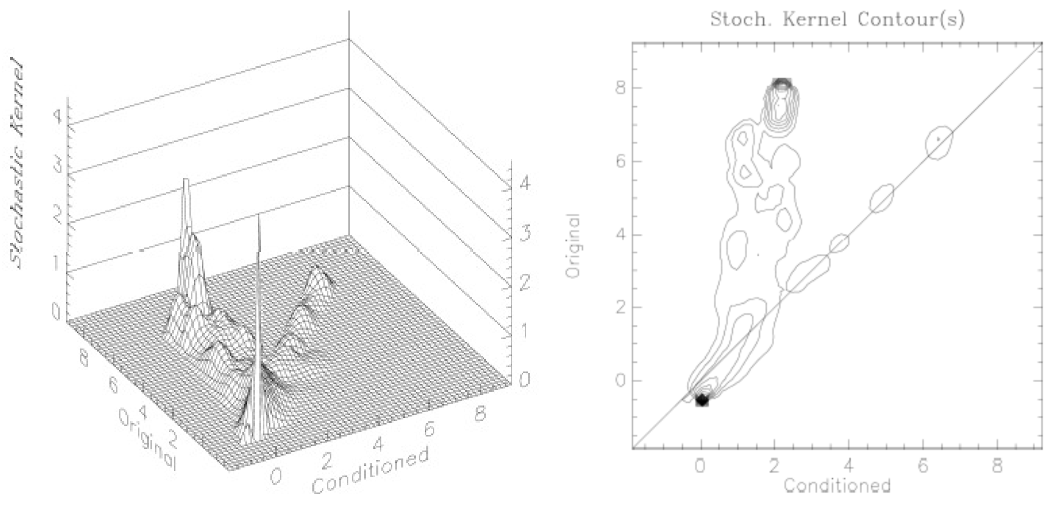


Figure 4.a – Agriculture GVA per employed, territorial distribution, 1980

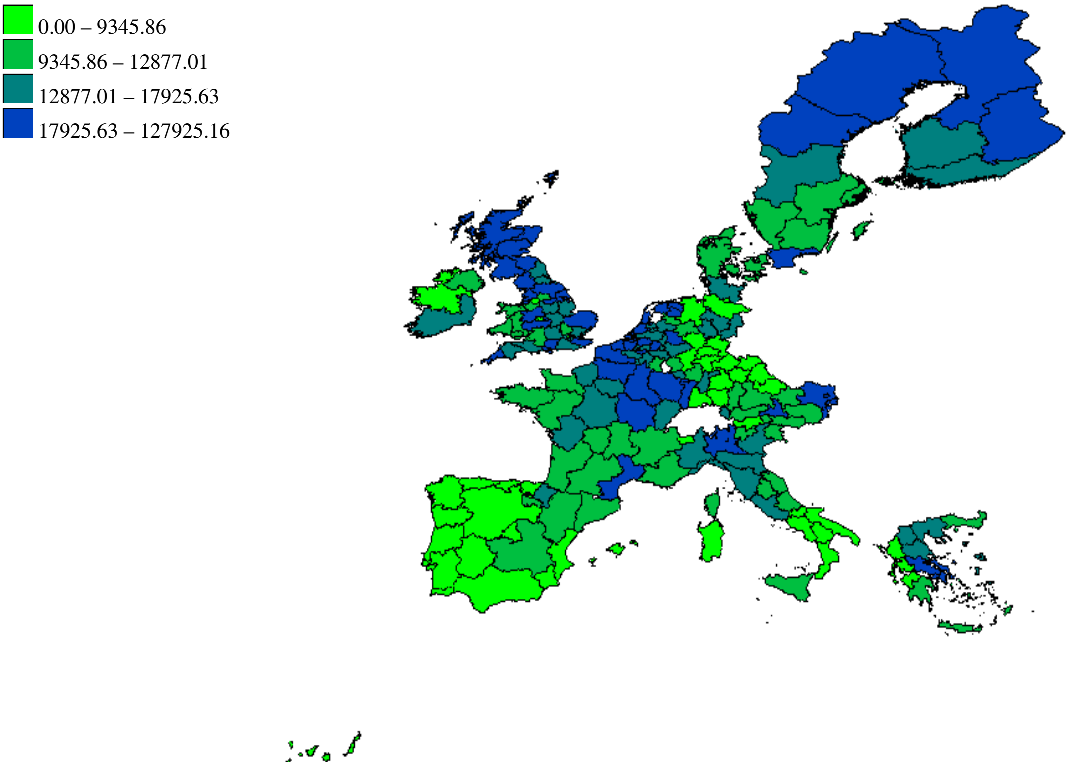


Figure 4.b – Agriculture GVA per employed, territorial distribution, 2005

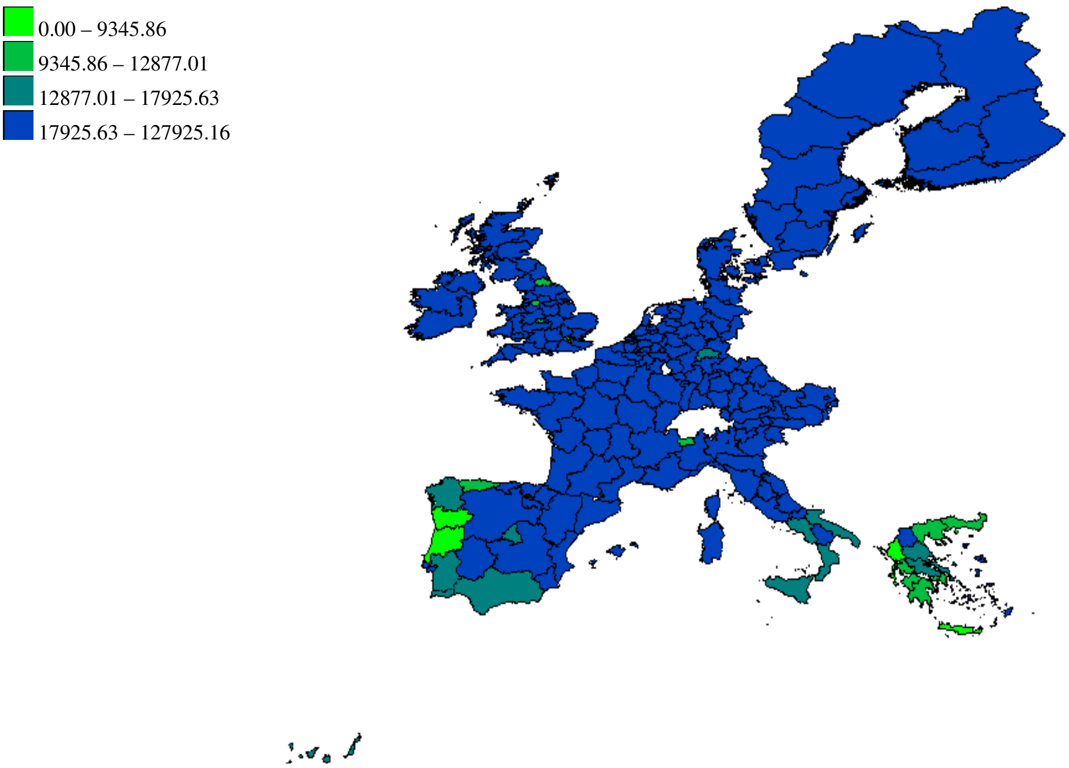


Figure 4.c – Agriculture GVA per employed, mean values across NUTS 2 sample

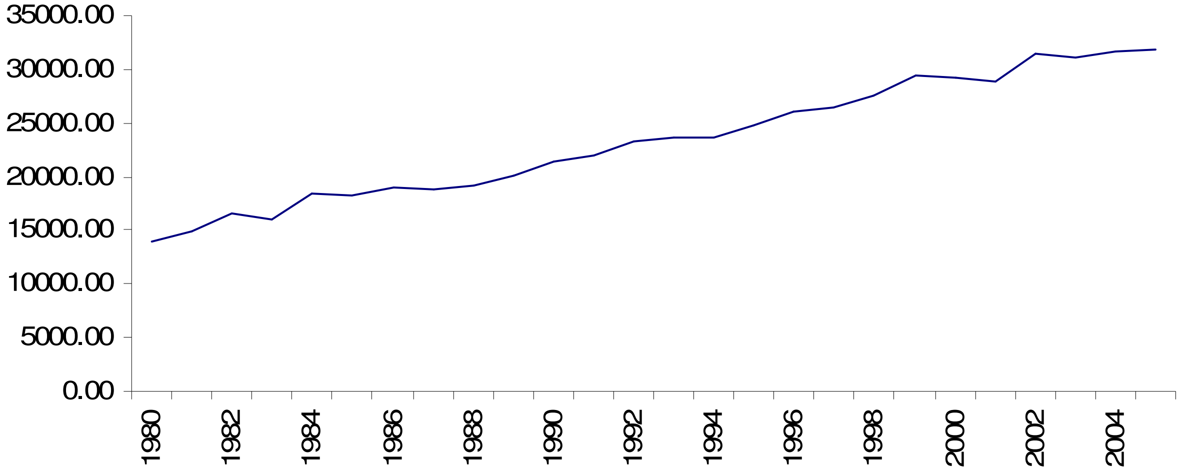
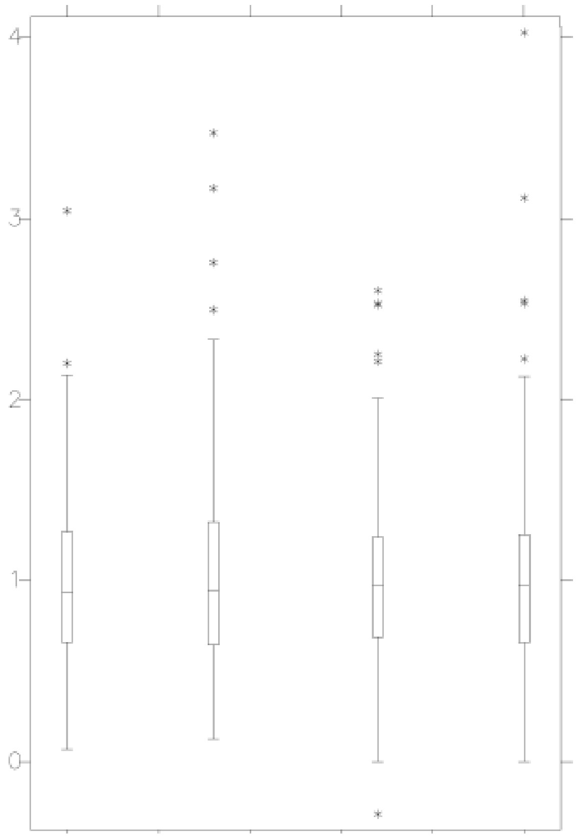
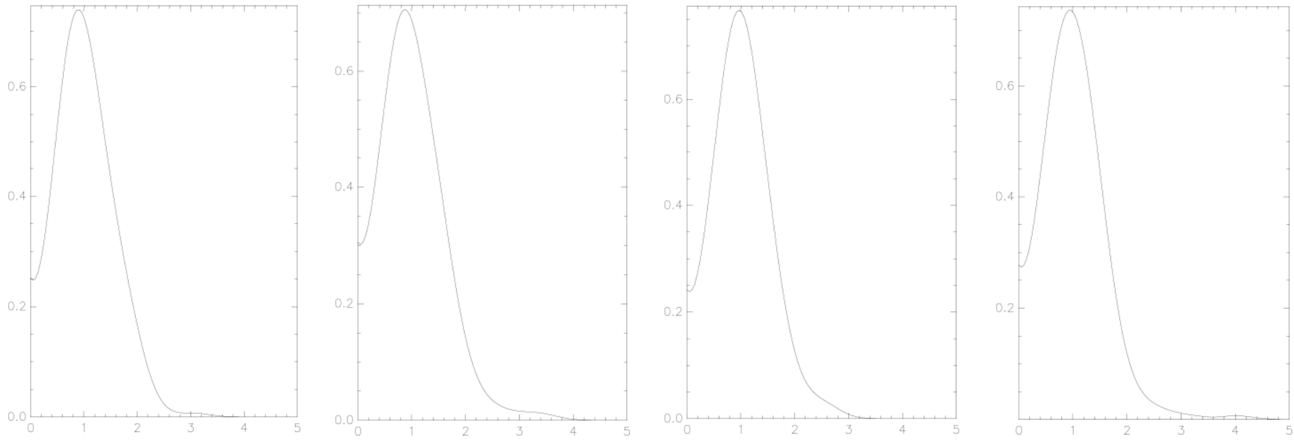


Figure 4.d – Tukey boxplot of relative agriculture GVA per employed



1980, 1988, 1997, 2005

Figure 4.e – Densities of relative agriculture GVA per employed



1980 1988 1997 2005

Figure 4.f – Stochastic kernel: relative agriculture GVA per employed distribution dynamics

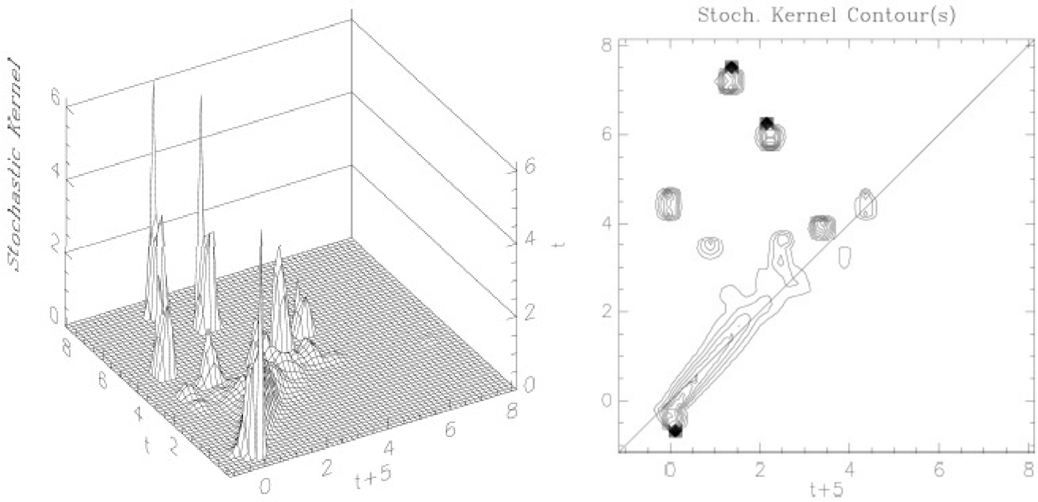


Figure 4.g – Stochastic kernel: relative agriculture GVA per employed distribution conditioned to spatial contiguity

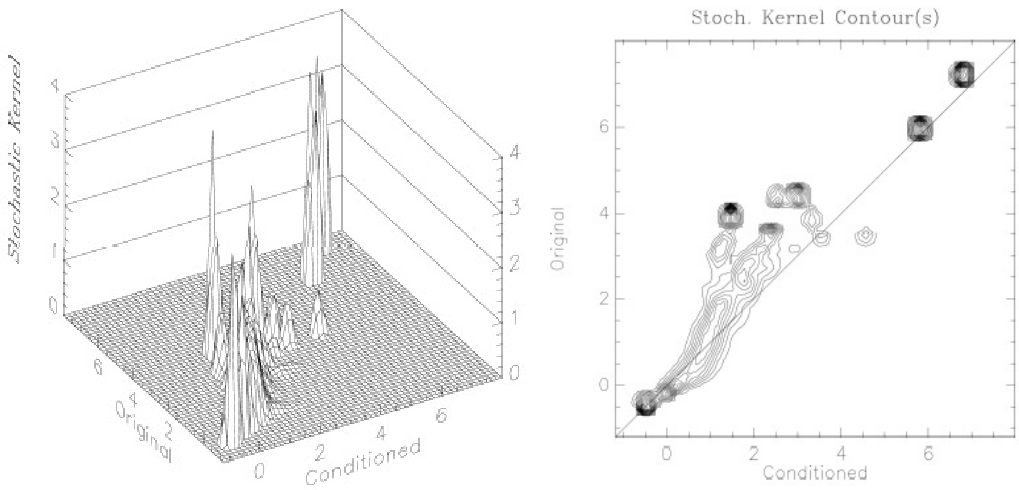


Figure 4.h – Stochastic kernel estimate: relative agriculture GVA distribution conditioned to the number of employed

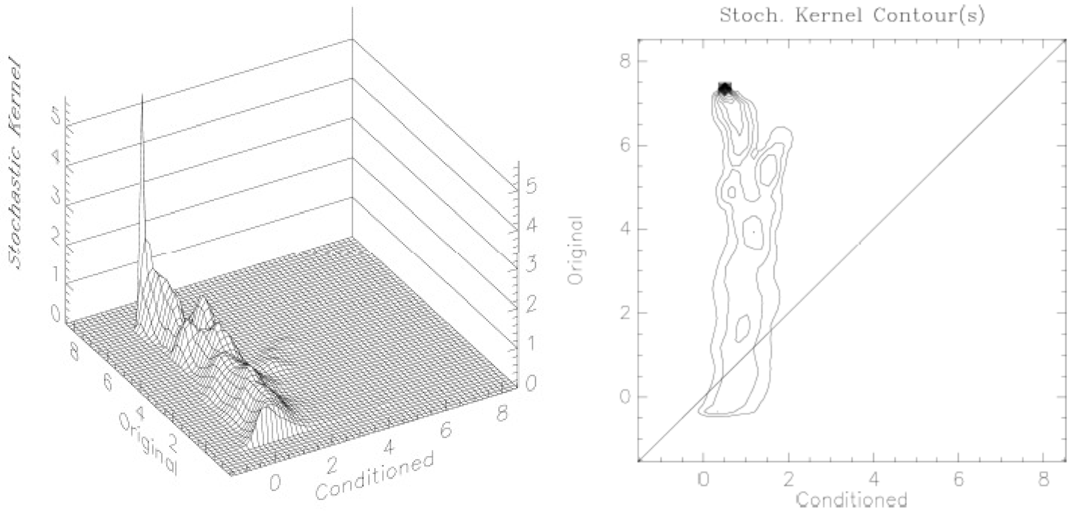


Figure 5.a – GVA / density of inhabitants ratio, territorial distribution, 1980

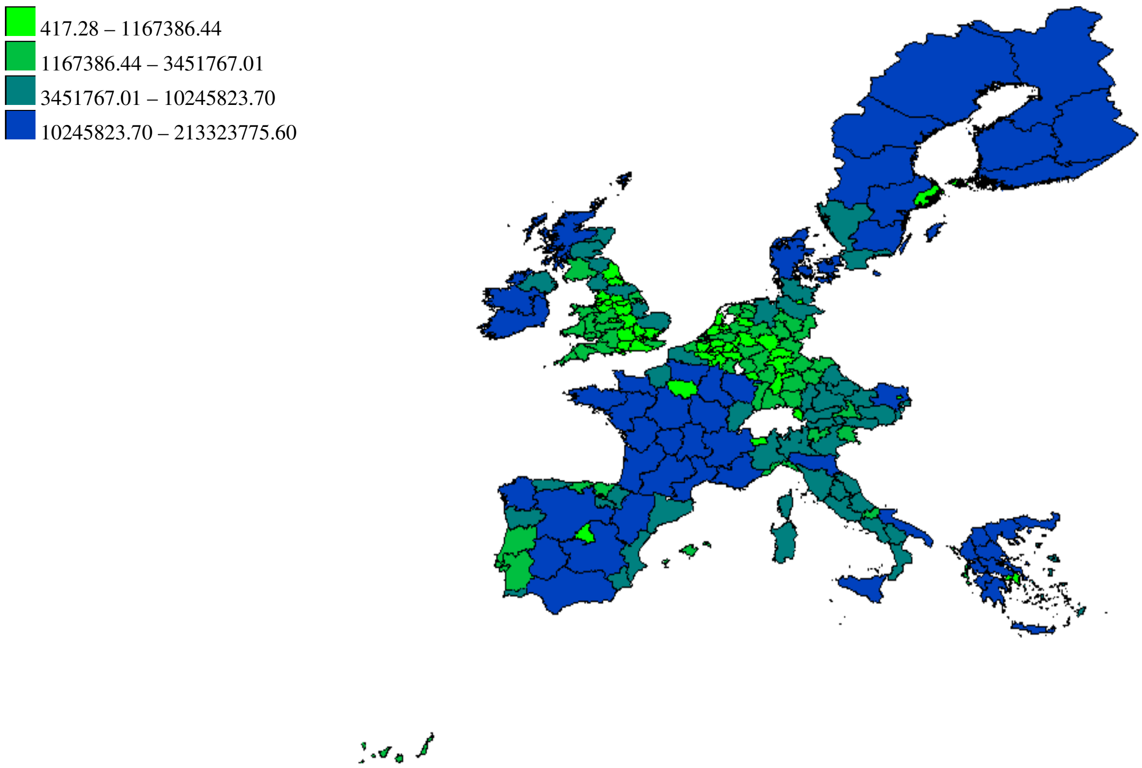


Figure 5.b – GVA / density of inhabitants ratio, territorial distribution, 2005

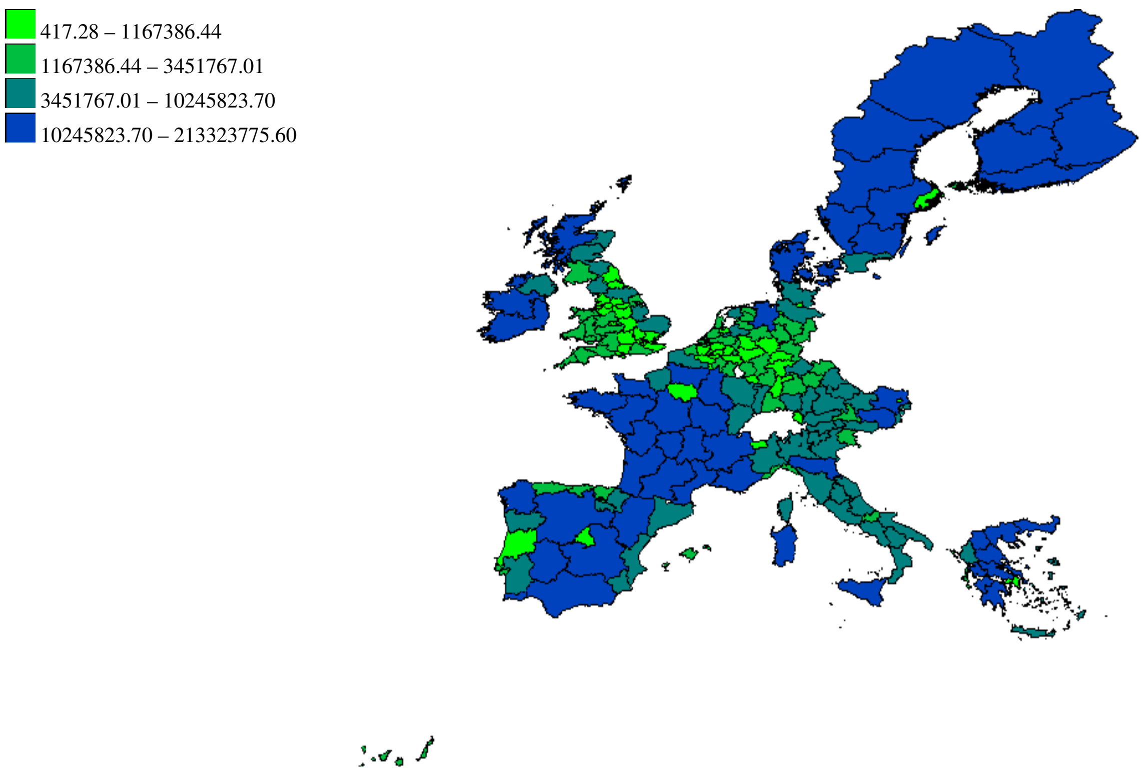


Figure 5.c – GVA / density of inhabitants ratio, mean values across NUTS 2 sample

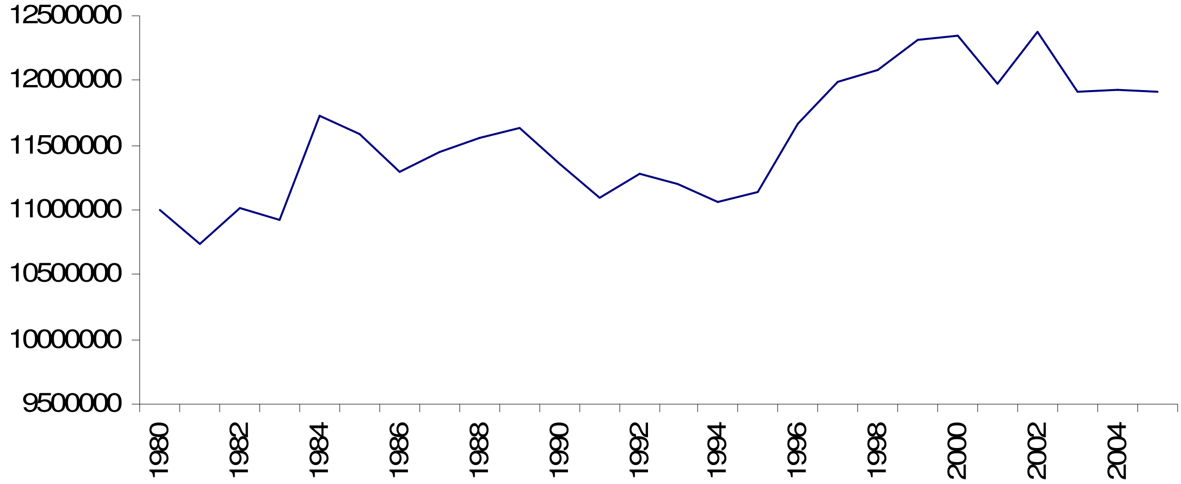
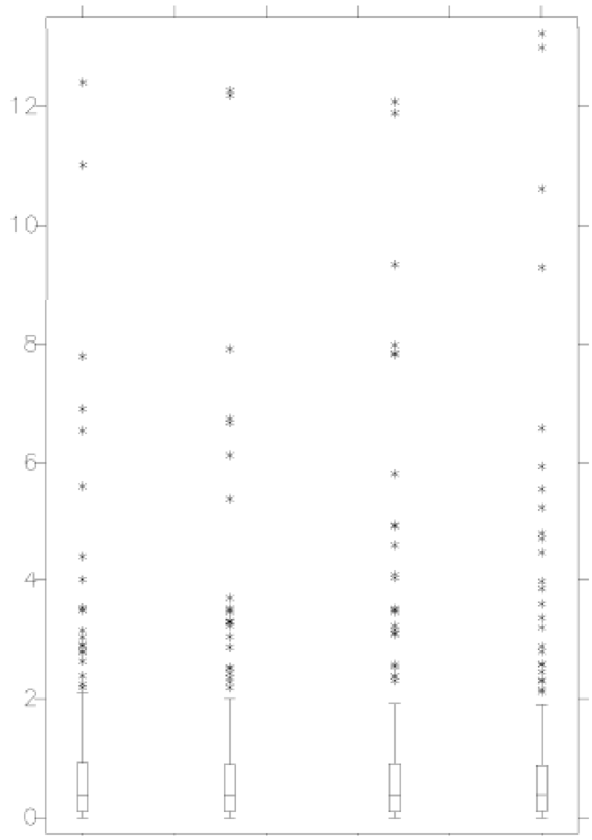
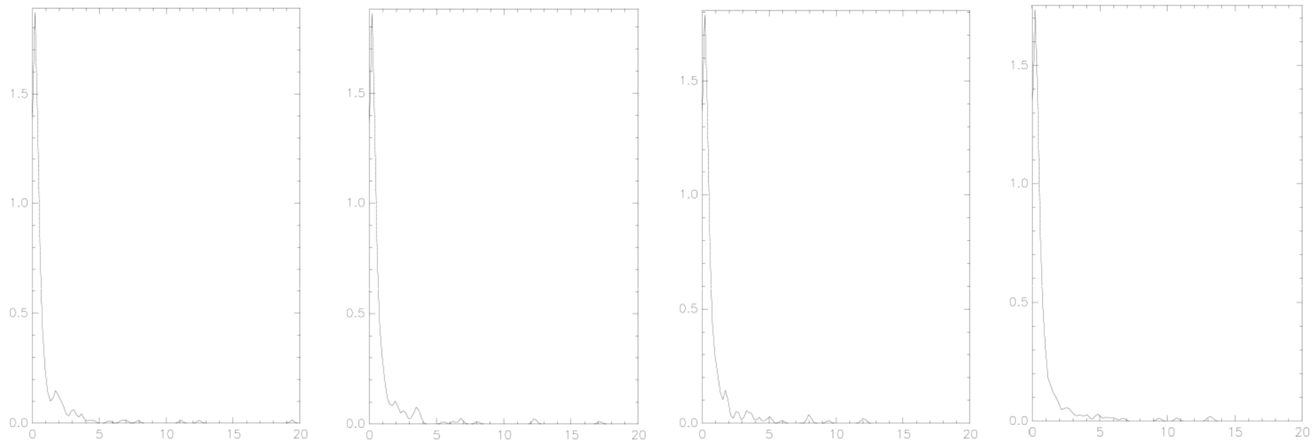


Figure 5.d – Tukey boxplot of relative GVA / density of inhabitants ratio



1980, 1988, 1997, 2005

Figure 5.e – Densities of relative GVA / density of inhabitants ratio



1980 1988 1997 2005

Figure 5.f – Stochastic kernel: relative GVA / density of inhabitants ratio distribution dynamics

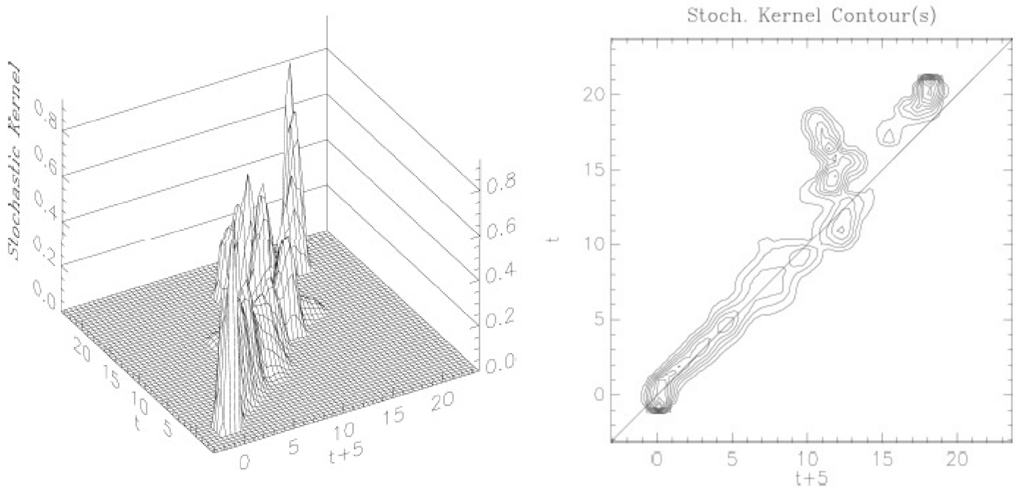


Figure 5.g – Stochastic kernel estimate: relative GVA / density of inhabitants ratio distribution conditioned to spatial contiguity