European Countries' Competitiveness and Productive Performance Evolution:

Unraveling the complexity[1]

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Abstract

European Countries Industrial Structures (CSIS) differential productive performance evolution is associated to the country specific competitiveness in a theoretical and empirical setting. Evolution patterns are decomposed into multifaceted heterogeneity, state and path dependence and growth patterns. Latent technology heterogeneity is introduced in the analysis employing a metafrontier framework which allows for the relaxation of the 'technological isolation' hypothesis. In this line, we hypothesize the existence of 'convergence clubs' within European Union. Autoregressive Latent Trajectory (ALT) model allows for the empirical investigation of a set of complex relationships between state and path dependence and growth patterns. Empirical results indicate that all three components of evolution significantly determine CSIS technology gap evolution patterns. We confirm the existence of two distinct convergence clubs within EU, the Industrial Leaders and Followers group. Last but not least, participating in Industrial Leaders or Followers Group significantly influences the corresponding EU country competitiveness.

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1. Introduction

Improving European countries' competitiveness has been an everlasting policy goal. In this line, National and European efforts have been directed in implementing policies aiming at a two-level end result; on one hand supporting at the national level sectoral competitiveness and at a second level achieving a catching-up rate for all European economies. However, empirical evidence suggests that among European countries specific industrial structures productive performance differentials exist which are mainly attributed to restricted access to different technologies (Syverson, 2011; Pianta, 2014). Such technology heterogeneity is translated in *technology gaps* among European countries that remain persistent over time.. The persistence of technology gaps among European countries industrial structures may be attributed to three main sources; (i) the rather persistent underlying technological *heterogeneity* (Dosi and Lechevalier, 2010) (ii) the *path and state dependent* processes (David, 1985; Antonelli, 2013), and (iii) the *growth patterns* of such technology evolution (Castellacci et al., 2014). Taken together, these three components synthesize the evolution patterns of Country Specific Industrial Structures (CSIS) technology Gaps which in turn elevates the complexity surrounding the processes with which firms, industries and eventually countries achieve their competitiveness (Arthur, 2013).

Exploiting a unique dataset of 17 European Countries and 13 industries of the Manufacturing, Transport and Construction sectors for the period 2000-2006, we investigate the evolution patterns of European Country Specific Industrial Structures (CSIS) productive performance employing a two-step novel methodology. At the first step, we estimate EU CSIS technology gaps arising in a metafrontier context, following closely (Kounetas et al. 2009).The introduction of metafrontier analysis as an approach that allows the investigation of the interrelationships between different technologies (Battese et al., 2004; O'Donell et al, 2008)) and can be used in order to explain differences in productive performance opportunities that can be attributed to available resource endowments, economic infrastructure, and other characteristics of the physical, social and economic environment in which production takes. In principle, the metafrontier context allows for the relaxation of the “technological isolation” assumption, widespread in the efficiency and productivity analysis literature. The downsizing of the technological isolation elevates the role of technology spillovers and of the absorptive capacity of industries and countries in the corresponding productive performance and ultimately in their competitiveness.

At a second step, we account for a complexity framework by estimating the evolution patterns of such technology gaps, taking into consideration all three sources of persistence of technology gaps, that is, heterogeneity dependence, and growth patterns, employing an *autoregressive latent trajectory* (ALT) model (Bollen and Curran, 2004) applying mixture modeling estimation techniques. In addition, the growth evolution of the technology gaps is associated with the EU countries’ competitiveness at the end of the examined period in order to determine whether technology gaps influence at the long run a country’s competitiveness (Landesmann and Robert, 2001). The ALT model incorporates features of both the autoregressive model and the latent growth curve model in a single framework.

The estimated model allows us to incorporate complexity by simultaneously estimating the latent growth factors of endogenously determined latent classes and more specifically of the the initial conditions and growth rate, the interrelation (covariance) between them, along with the effect of the path and state dependency. *Empirical results reveal that all three sources of persistence indeed play a significant, although distinctive, role in determining the growth evolution of technological gaps in European countries and industries*. Therefore the convergence

– divergence issue, within the unified European economy, becomes a multifaceted phenomenon. More specifically, two groups of European industries are identified sharing commonalities in the growth evolution pattern of technology gaps, thus allowing us to minimize the intra-class heterogeneity of the growth evolution patterns. Moreover, path and state dependence prove also to be major determinants is of the growth process. Last but not least, both identified groups of European industries evolution patterns influence positively their corresponding country competitiveness at the end of the observation period. Intra- and inter-group catching up or falling behind phenomena are further investigated.

The rest of the paper is organized as follows; section 2 reviews the relevant literature and puts forward the theoretical considerations and testable hypotheses while section 3 is devoted in presenting the adopted two-step methodological approach; section 4 presents the employed information in the estimation processes and section 5 discusses the empirical findings. Section 6 concludes the paper.

2. Theoretical Framework and hypotheses for testing

This section reviews the relevant literature and highlights the complexity surrounding the processes of defining technology gaps, and investigating their evolution as well as patterns of catching-up and convergence. We adopt the view that the economy should not be considered at given state with an implied equilibrium, but rather it should be perceived as a perpetually forming and adjusting mechanism from a constantly developing set of technological innovations, institutions, and arrangements that draw forth further innovations, institutions and arrangements (Arthur, 2013).

2.1 Investigating the existence of heterogeneity in the evolution patterns of technology gaps

Within the context of the evolutionary economics literature investigating international competitiveness, the notion of technology gaps has emerged (Posner, 1961; Dosi and Soete, 1983). Despite the fact that its emergence has occurred in the context of the trade literature and in particular the New Trade Theory (Krugman, 1985) and New New Trade Theory (Melitz, 2003), its contribution lies in the fact that it highlights the sources of persistent differential patterns of (productive) performance which eventually determine international competitiveness based on technological advantages or disadvantages. In the same spirit, the technology gap approach allows for the relaxation of the "technological isolation" assumption –i.e. the identical production technologies which allow a direct comparison of the benchmark type- and the resulting absence of spillovers and absorptive capacity. Moreover this approach incorporates the effects of multidirectional technology and knowledge flows and spillovers in shaping industrial, sectoral and country level productive performance (Hayami and Rutan, 1970; O' Donnell et al., 2008). In essence, CSIS technology gaps allow for technology and knowledge spillovers within and between EU countries, however they are *latent*; their influence is reflected indirectly in the productive performance of EU industrial structures. In this respect, the technology gap approach may be considered as an appropriate index for the evaluation of EU industrial structures performance by considering simultaneously the status of technology and production markets of within a particular EU country/industry and a pan-European technology and production market. In other words, there may exist a *within* and *between* technological heterogeneity in determining EU industries' productive performance (Bos et al., 2010).

European Country specific industrial structures (CSIS) encompass the inherent technological heterogeneity attributed to social, institutional political and economic factors

(Kounetas et al., 2009). Such a technological heterogeneity may be in turn reflected in the evolution patterns of EU countries' productive performance, and specifically in the rate of convergence among EU countries. As a result and from a dynamic perspective, European CSIS change and evolve causing an structural change in the sectoral composition of European economies (Caccomo, 1996). *Therefore, the evolution of technology gaps provides evidence on the degree of integration and convergence among European industrial structure and consequently among EU economies (Fagerberg, 2000).* In other words, it could be argued that the EU CSIS technology gaps evolution reflects a *directional* structural change which is grounded on the interplay between the change in the sectoral composition of an economic system, and technological change (Malerba, 2007; Quatraro, 2012). Based on the above the following hypotheses are formed:

> *H_1: The evolution patterns of EU countries' technology gaps are heterogeneous*
>
> *H_2: The evolution of Technology gaps are determined by EU countries' sectoral composition*

2.2 Investigating the existence of state and path-dependence on the evolution patterns of technology gaps

The catching-up hypothesis (Gerschenkron, 1962) presumes that being backward in the level of productive performance carries a potential for rapid advance forward and upward. However, the pace of realization of catching-up rates is mostly dependent upon the conditions that rule the technology and knowledge flows such as absorptive capacity and strategic orienatation, the rate of structural change, the accumulation of capital the expansion of demand

(Abramovitz, 1986; Kontolaimou and Tsekouras, 2010). In particular, across EU countries' industrial structures, the evolution patterns of the corresponding technology gaps that is the shape of the growth curve and the role of state and path dependency, are expected to be inversely related to the initial levels of technology gaps provided that the EU countries' industrial structures possess the capacity to exploit the emerging opportunities and thus, boost their competitiveness (Fagerberg et al., 2007; Veugelers and Mrak, 2009).

However, as it has been argued above, the CSIS productive performance reflects an idiosyncratic pattern of technological heterogeneity which in turn may be attributed to country specific processes to attain competitive gains. Put differently, it may be the case that within the EU, "convergence clubs" exist (Ben-David, 1994; Castellacci et al., 2014) that is group of countries that converge locally but not globally. More specifically, the existence of convergence clubs presupposes that *initial conditions* of CSIS technology gaps do matter in the long run and those EU countries with similar initial conditions will exhibit similar long-run outcomes thus, forming *convergence clubs* (Pittau et al., 2010). Such being the case, a structural gap denoting the distance between the groups of countries is necessary to exist. Therefore, group membership may indirectly specify the evolution of the country's productive performance. In addition, within each convergence club the similarity in the evolution patterns of EU CSIS technology gaps could well be a case of the importance of a path-dependent development with possibilities of lock-in (Arthur, 1986; Perez and Soete, 1988). Based on the above the following hypothesis is formed:

> *H_3: The evolution of technology gaps of EU countries industrial structures is state and path dependent.*

2.3 The relationship between the technology gaps evolution and EU countries competitiveness

Figure 1 summarizes the theoretical considerations analyzed above. Thus far, we have argued that the multilevel technological heterogeneity as well as state and path dependence jointly influence the evolution patterns of Technology Gaps of EU countries' industrial structures. In this line, one more thing remains to be addressed and specifically the potential influence of the evolution patterns of Technology gaps on EU countries on their competitiveness. The notion competitiveness is a quite flexible term; it may be employed at different levels of aggregation and reflect different components of the overall economic ability to compete (Fagerberg, 1996; Fagerberg et al, 2007). It should be noted that competitiveness is multifaceted and decomposed in several components. Especially at an aggregate level, a country's competitiveness does not only reflect the crude numbers of economic wealth but also other qualititative aspects (Delgado et al., 2012).

{Insert Figure 1 around here}

Previous research efforts have focused in identifying the role of the evolution of EU CSIS productive performance on their competitive position, or in other words whether the underlying technological heterogeneity (Bos et al., 2010), as well as the state and path dependence of technology gaps (Pittau et al., 2010; Antonelli et al., 2013) determine whether a country may improve its competitive position. In this line we form the following hypothesis:

H_4: The evolution patterns of Technology gaps determine the EU countries' competitiveness at the end of the observation period.

3. Methodological Underpinnings

3.1. The metafrontier context

A multiple-input, one-output production technology, where inputs $x \in R_+^n$ are used in the production of $y \in R_+^m$ output for thirteen different industries of seventeen European countries can be represented by the production set $S = \{(x, y) : x \text{ can produce } y\} \subseteq R_+^{n+m}$ of attainable input-output combinations while the input set, is defined as $L(y) = \{x \in R_+^n : (x, y) \in S\}$. The technology is assumed to satisfy a set of axioms discussed in Shepard (1953; 1970) referring that i) inactivity is allowed, ii)"free lunch" is not allowed iii) technology is convex and iv) strong disposability of inputs and outputs.

In the framework of i industries the input-oriented efficiency associated with S can be measured with respect to the input set through the direct *input distance function* $D_I(x, y) = \sup\{\theta > 0 : x|\theta \in L(y)\}$. Thus the productive efficiency for a given industry (x, y) in each one of the examined European countries is given as Eq.(1):

$$\hat{Eff}_{i|k}(x, y) = \min\{\theta \Big| \theta > 0, y_i \leq \sum_{i=1}^{n} \gamma_i y_i ; \theta_x \geq \sum_{i=1}^{n} \gamma_i x_i \text{ for } \gamma_i \text{ such that} \\ \sum_{\mathrm{i}=1}^{\mathrm{n}} \gamma_i = 1; \gamma_i \geq 0, i = 1,2,\ldots,n\} \tag{1}$$

The specific measure allows us to estimate the productive efficiency of each industry i located at its own country-frontier. However, it is not possible to compare industries belonging to different countries taking into account the case where multiple technologies are possible and available. Relaxing this hypothesis, the notion of the metafrontier comes into play providing a benchmarking for all the participating industries independently from the frontier that each belongs.

Hence, given k technologies $T^1, T^2, ..., T^k$ the metatechnology set, denoted as T^M, can be defined as the convex hull of the jointure of all technology sets represented as

$T^M = \{(x, y : x \geq 0, y \geq 0,\ x$ can produce y in at least one of $T^1, T^2, ..., T^k\}$ (Rao et al., 2003) - i.e. a global frontier that envelopes each of the k individual country frontiers. The input set $L^M(x)$ associated with the metatechnology is defined in the same way as for a single technology, while the corresponding efficiency of each industry with respect to homogeneous boundary for all heterogeneous industries can be measured by the input-oriented metatechnical efficiency score $MTEff_{i|k}$ and is easily obtained by solving an analogous LP problem as in Eq.(1).

The introduction of metafrontier analysis as an approach that allows the investigation of the interrelationships between different technologies (Battese et al., 2004) can be used in order to explain differences in production opportunities that can be attributed to available resource endowments, economic infrastructure, and other characteristics of the physical, social and economic environment in which production takes (O'Donnell et al., 2008; Kontolaimou et al., 2012), structure of national markets, national regulations and policies, cultural profiles and legal and institutional frameworks (Halkos and Tzeremes, 2011) and different rate of access and acceptance of General Purpose Technologies-GPT (Kounetas et al., 2009). O' Donnell et al. (2006) extended the Battese et al. (2004) framework using conventional Shepard distance functions to estimate technical efficiency with respect to that metatechnology and several individual technology sets. Each productive efficiency score obtained from the estimation with respect to the common technology can be used to define the so-called metatechnology ratio $MTR_{i|k}$ which is considered as a measure of proximity of the *k*-th group individual frontier to its metafrontier. For a given point (x, y), the latter could be defined as in Eq.(2):

$$MTR_{i|k}(x, y) = \frac{MTEff_{i|k}(x, y)}{Eff_{i|k}(x, y)} \tag{2}$$

$MTR_{i|k}(x,y)$ depicts the ratio of the minimum inputs attained by a industry employing the superior metatechnology to the minimum inputs used by the group technology to produce a given level of outputs. Taking advantage of the $MTR_{i|k}$ notion, the technology gap $(Tg_{i|k})$of the *i*-th industry in the *k*-th group frontier is defined as the distance of the group frontier to the metafrontier, weighted with the minimum inputs which are attainable employing the group-specific technology, that is (Eq.3):

$$Tg_{i|k}(x,y)=1-MTR_{i|k}(x,y) \qquad (3)$$

For an industry exhibiting a $Tg_{i|k}$ value equal to zero, it is evident that the group frontier, at the input level of the specific industry, is tangent to the metafrontier and thus no efficiency losses are due to inferiority of the group technology compared to the metatechnology. However productive inefficiency with respect to the group frontier is still a possible situation.

Simar and Wilson (1998, 2000, 2007) suggested that DEA estimators were shown to be biased by construction. They introduce an approach based on bootstrap techniques (Efron, 1979) to correct and estimate the bias of DEA estimators. The basic idea of the bootstrap method is to approximate the sampling distributions of the estimator using the empirical distribution of the resampled estimates obtained from a Monte Carlo simulation of the estimation procedure where the repeated resamples have been obtained from an estimate of the data generating process (DGP) produce repeated estimates.

Following closely Simar and Wilson's procedure we are able estimate the bias estimate for the original DEA estimator $bias_i = \frac{1}{B}\sum_{B=1}^{K} eff^{*}_{i|k,B}(x,y) - eff_{i|k}(x,y)$ (4) where B[3] the number of

[3] At least equal to 2000, to get reasonable Monte Carlo approximations even in the tails of the distribution

bootstrap replications. Consequently a bias corrected estimator of $eff^{*}_{i|k,B}\left(x,y\right)$ is given as follows:

$$eff^{*}_{i|k,B}\left(x,y\right)=eff^{*}_{i|k,B}\left(x,y\right)-bias_{i}\,eff^{*}_{i|k,B}\left(x,y\right)=2eff_{i|k,B}\left(x,y\right)-\frac{1}{B}\sum_{B=1}^{K}eff^{*}_{i|k,B}\left(x,y\right)\ (5).$$

3.2. Autoregressive Latent Trajectory (ALT) mixture model

In economics, *change* is exclusively modeled and analysed via the longitudinal panel data methods (Wooldridge 2010, Greene, 2008). However, the creation of the "best methods" for the analysis of change has been a continuing concern in many research disciplines other than economics. For instance, in the context of behavior and developmental research Baltes and Nesselroade (1979) outlined five key objectives for longitudinal research: *(i)* direct identification of intra individual change, *(ii)* direct identification of inter-individual differences in intra-individual change, *(iii)* analysis of interrelationships in change, *(iv)* analysis of causes (determinants) of intra-individual differences and *(v)* analysis of causes (determinants) of inter-individual differences in intra-individual change.

Within this context, two independently developed methodological approaches, namely *the autoregressive model* (Kessler and Greenberg, 1981; Ahn and Schmitd, 1995, 1997) which is widely employed in dynamic panel analysis, and *the latent trajectory (curve) model* (Meredith and Tisak 1990; Duncan and Duncan 1994), have dominated the modeling of change. A distinguishing feature of the autoregressive models is that they allow the prior value to determine the current value of the same variable. In contrast, the latent trajectory (growth) model allows separate (individual) trajectories over time for repeated measures. Bollen and Curran (2004) recently proposed the Autoregressive Latent Trajectory (ALT) [4] model which is a synthesis of the two methodological approaches, leading to a flexible hybrid model.

With respect to the second part of the ALT model, the latent growth curve modelis a methodological framework employed in the social sciences and aims at studying the growth process of a key indicator. The growth process is assumed to be composed of two main sources and specifically, the initial state upon which the indicator under investigation is firstly observed and the corresponding growth rate. Further below we present analytically the ALT model specification interested in modeling the evolution patterns of Technology Gaps. Let us begin from the autoregressive part of the model; the estimated equation for the simplest autoregressive model is

$$TG_{it} = \alpha_t + \rho_{t,t-1} TG_{i,t-1} + \varepsilon_{it} \tag{4}$$

where $E\left(\varepsilon_{it}\right)=0$ for all *i* and *t*, $COV\left(\varepsilon_{it}, TG_{i,t-1}\right)=0$ for all *i* and *t=2,3…T*, $E\left(\varepsilon_{it}, \varepsilon_{jt}\right)=0$ for all *t* and $i \neq j$, and $E\left(\varepsilon_{it}, \varepsilon_{jt}\right)=\sigma_{\varepsilon_t}^2$ for all *t* and $i=j$, and $E\left(\varepsilon_{it}, \varepsilon_{j,t+\kappa}\right)=0$ for all κ and $i \neq j$. Though it is possible to allow for autoregressive disturbances to keep the model simple we follow the predominant practice and assume non-autocorrelational disturbances ($E\left(\varepsilon_{it}, \varepsilon_{i,t+k}\right)=0$ for $\kappa \neq 0$). The α_t is the intercept for the equation at time *t*. The $\rho_{t,t-1}$ is the autoregressive parameter. It models the impact of the Technology gap of the previous period on the current one, or in other words *it models the path-dependent evolution of Technology gaps*.

Turning to the univariate Latent Trajectory Model, Equation (5) below models the evolution patterns of EU countries' industrial structures Technology gaps. Specifically the evolution patterns

[4] This model does not assume the existence of subpopulations (i.e. groups) within the sample. Further below we will present the employed Finite Mixture Modeling method of estimation of the presented ALT model.

of EU countries' industrial structures Technology gaps may be decomposed in two components, the initial state and the rate of growth:

$$TG_{it} = \alpha_i + \Lambda_{t2}\beta_i + \varepsilon_{it} \qquad (5)$$

where α_i is a random intercept for the *i*-th industry belonging to a particular EU country approximating the initial state, and β_i is the random slope for *i*-th industry belonging to a particular EU country, approximating the rate of growth. The Λ_{t2} is a constant within time *t*, where $\Lambda_{12} = 0$, $\Lambda_{22} = 1$. The remaining values of Λ_{t2} allow for the incorporation of linear and non linear trajectories. Essentially, Λ_{t2} parameter models the development of time[5] in relation to the growth patterns of Technology Gaps. In this particular case examined time is modeled with a log-linear form[6]. We assume that $E(\varepsilon_{it}) = 0$ for all *i* and *t*, $COV(\varepsilon_{it}, \beta_t) = 0$ and $COV(\varepsilon_{it}, \alpha_t) = 0$ for all *i* and *t=2,3…T*, $E(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for all *t* and $i \neq j$, and $E(\varepsilon_{it}, \varepsilon_{it}) = \sigma^2_{\varepsilon_t}$ for each *t*. Also it is assumed that $E(\varepsilon_{it}, \varepsilon_{i,t+k}) = 0$ for $\kappa \neq 0$ so that the errors are not correlated over time. The latent trajectory model allows each industry *i* to have a distinct intercept and slope to describe the trajectory of Technology Gap over time *t*. This is captured by indexing the Technology Gaps intercept (α_i) and slope (β_i) by *i* to highlight that they can differ across industries. It should also be noted that the Technology Gaps intercept (α_i) and slope (β_i) are latent variables. The mean intercept and mean slope are on interest and are expressed as

[5] There is a variety of ways to model time in the context of the Latent Trajectory model however, such kind of exploration is beyond the scope of the present research. For a more detailed presentation on this issue see Wang and Wang (2012) p. 142-183.

[6] Many other alternatives for modeling time have been employed but the log-linear form of time is the most representative of the Technology Gaps evolution based also on model fit indices.

$$\alpha_i = \mu_\alpha + \zeta_{\alpha i} \tag{6}$$

$$\beta_i = \mu_\beta + \zeta_{\beta i} \tag{7}$$

where μ_α and μ_β are the mean Technology Gap intercept and slope across all EU countries' industrial structures. The $\zeta_{\alpha i}$ and $\zeta_{\beta i}$ are disturbances with means of zero and uncorrelated with ε_{it}. They represent the random variability around the mean intercept and mean slope and we allow $\zeta_{\alpha i}$ and $\zeta_{\beta i}$ to be correlated.

Contrasting the autoregressive model to the latent trajectory one, it becomes evident that equation (4) and equations (5)-(6) hypothesize different relationships between the variables. The autoregressive model gives primacy to lagged influences and fixed effects whereas the latent trajectory model focuses on individual differences in growth trajectories over time. It is therefore, their combination which is of interest in this particular paper. More specifically, from the latent trajectory model the random intercept and slope factors are incorporated to capture the fixed and random effects of the underlying Technology Gap trajectories over time. From the autoregressive model, the standard fixed autoregressive parameters are included in order to capture the time specific influences between the repeated measures themselves. Therefore, the ALT equation for the Technology Gaps of the EU countries industrial structures is

$$TG_{it} = \alpha_i + \Lambda_{t2}\beta_i + \rho_{t,t-1}TG_{i,t-1} + \varepsilon_{it} \tag{7}$$

where $t=2,3...T$, $E(\varepsilon_{it}) = 0$, $COV(\varepsilon_{it}, \beta_t) = 0$ and $COV(\varepsilon_{it}, \alpha_t) = 0$ and $COV(\varepsilon_{it}, TG_{i,t-1}) = 0$. It is also assumed that $E(\varepsilon_{it}, \varepsilon_{jt}) = 0$ for all t and $i \neq j$, and $E(\varepsilon_{it}, \varepsilon_{it}) = \sigma^2_{\varepsilon_t}$ for each t. In addition, as was the case in the autoregressive model we assume non-autocorrelated disturbances (i.e. $E(\varepsilon_{it}, \varepsilon_{i,t+k}) = 0$ for $\kappa \neq 0$). It becomes clear that the ALT model permits lagged values of

Technology Gaps to influence current values and the same time that the growth trajectory of Technology Gaps is in part governed by the random intercept (i.e. initial state) and slope (i.e rate of growth). As with the standard latent trajectory model, the random intercept and slope components can be expressed as a function of their corresponding mean and disturbance terms. In addition we have incorporated two time invariant exogenous predictors z_{i1} and z_{i2} which reflect the sectoral composition of EU economies. Equations (5) and (6) thus become

$$\alpha_i = \mu_\alpha + \gamma_{\alpha 1} z_{i1} + \gamma_{\alpha 2} z_{i2} + \zeta_{\alpha i} \tag{8}$$

$$\beta_i = \mu_\beta + \gamma_{\beta 1} z_{i1} + \gamma_{\beta 2} z_{i2} + \zeta_{\beta i} \tag{9}$$

where the four gamma parameters $\left(\gamma_{\alpha 1}, \gamma_{\alpha 2}, \gamma_{\beta 1}, \gamma_{\beta 2}\right)$ represent the fixed regressions of the random intercept and slope components on the two correlated exogenous predictors. It should be noted that these regression parameters are fixed and represent the shift in the conditional means of the random trajectory parameters as a function of the explanatory variables.

At this point the issue of the first time point should be examined more closely. Even though it has been suggested to treat TG_{i1} as predetermined we have opted to treat it as endogenous to the model. In such a case the equation for the first time period becomes

$$TG_{i1} = \Lambda_{11}\alpha_i + \Lambda_{12}\beta_i + \varepsilon_{i1} \tag{10}$$

Another level of sophistication is added when it is assumed that the sample under investigation is derived from a heterogeneous population with different distributions. This particular type of heterogeneity may be investigated employing a mixture modeling approach.

One final issue remains to be addressed regarding the employed methodology in estimating the evolution patterns of EU industrial structures technology gaps. More specifically, another level of sophistication is added when it is assumed that the sample under investigation is derived from a heterogeneous population with different distributions. In order to detect technological heterogeneity both with respect to the initial state but also with respect to the rate of growth of CSIS Technology gaps a mixture modeling approach seems appropriate. Therefore, we estimate the above ALT model employing finite mixture modelling estimation methods (McLachlan and Peel, 2005) where essentially industries are classified in classes *k* depending on their intercept and slope. The ALT model thus becomes

$$TG_{it}^{k} = \alpha_{i}^{k} + \Lambda_{t2}^{k}\beta_{i}^{k} + \rho_{t,t-1}^{k} TG_{i,t-1}^{k} + \varepsilon_{it}^{k} \quad (11)$$

with mean intercept and slope structure

$$\alpha_{i}^{k} = \mu_{\alpha}^{k} + \gamma_{\alpha 1}^{k} z_{i1}^{k} + \gamma_{\alpha 2}^{k} z_{i2}^{k} + \zeta_{\alpha i}^{k} \quad (12)$$

$$\beta_{i}^{k} = \mu_{\beta}^{k} + \gamma_{\beta 1}^{k} z_{i1}^{k} + \gamma_{\beta 2}^{k} z_{i2}^{k} + \zeta_{\beta i}^{k} \quad (13)$$

with *t=1*

$$TG_{i1}^{k} = \Lambda_{11}^{k}\alpha_{i}^{k} + \Lambda_{12}^{k}\beta_{i}^{k} + \varepsilon_{i1}^{k} \quad (14)$$

This model is extended by including an outcome that is predicted from the growth patterns. Such an outcome is often referred to as a *distal outcome* (Muthén, 2004). In our case, the potential *competitiveness gains*, as they are approximated by a modification of the GC index is the modeled the distal outcome of the catching up process through the evolution of Technology Gaps. Given that the growth is succinctly summarized by the latent trajectory class variable, it is natural to let the latent trajectory class variable predict the distal outcome. With the example of a dichotomous distal outcome $COMPET$, this model part is given as a logistic regression with covariates *c* and *x*,

$$P\left(COMPET_I \left| c_i = k, \mathbf{x_i}\right.\right) = \frac{1}{1+e^{\tau_k - \kappa_k \mathbf{x_i}}} \tag{15}$$

where the main effect of *c* is captured by the class varying thresholds *τk* (an intercept with its sign reversed), and *κk* is a class-varying slope for x_i *x*. Equations (11)-(15) are estimated simultaneously employing full information maximum likelihood with robust standard errors.

4. Data and Variables

In order to test our methodological approach we employ a dataset that allows (i) introducing some apparent but meaningful DMU associated heterogeneity (ii) examining different technology hierarchies without involving any micro-level idiosyncrasies but in conjunction to DMU specific heterogeneity (iii) minimizing measurement errors that would increase DMU specific heterogeneity. In this direction we have device, the employed in this paper dataset, combining information provided by four distinct publicly available sources resulting in a unique balanced panel comprising of 13 2-digit industries[7] according to the International Standard Industrial Classification (ISIC) in 17 EU countries[8] over an 8-year period from 1999 to 2006. Thus, the employed dataset contains 221 observations on the cross section dimension and 1,768 observations on a panel data dimension.

The final dataset embraces five variables; one output and four input variables. More specifically, we approximate the output variable (*Y*) by the gross valued added of each industry, whilst the inputs include the capital stock (*K*) in million Euros, the labor input (*L*) which is captured by the total hours worked by employees, expenditure on intermediate inputs (*M*) in

[7] More specifically, 9 of them belong to the manufacturing (food and beverages, textiles, wood, pulp, chemicals, other non-metallic, basic metals, transport equipment) and 4 to the transportation sector (land transport, water transport, air transport and supporting and auxiliary transport activities)
[8] In particular, Belgium, Czech Republic, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Netherlands, Austria, Poland, Slovenia, Slovakia, Finland, Sweden, United Kingdom

million Euros and the total energy consumption (*E*) measured in million tons (Mt) of oil equivalent. For several of the countries[9] in this dataset, certain variables are reported in local currency, and need to be converted into Euro's before being used in the analysis.

Furthermore, we have employed as additional explanatory variables, the industry specific productive characteristics captured by the corresponding input ratios, and variables which capture any ambient technological discrepancies. These include the variables, GCI, which reflects the Global Competitiveness Index value of each country in the year 2006 and takes the value of one in case it exceeds the median value with respect to all the countries and zero otherwise, by a dummy, the $D_{Manufacturing}$ indicating whether the respective industry belongs to the manufacturing or not, the $D_{Transportation}$ reflecting industry's participation to the transportation sector or not while we also include the $D_{Construction}$ dummy variable as the reference group, indicating industry's participation to the construction sector. The former is intended to control for any heterogeneity owing to transaction cost advantages accruing to the countries participating in the EMU, while the latter were introduced in order to reflect differences in productive performance that may derive from each countries' relative advantages in infrastructure, human capital, technological achievements and other developments related to the production process (Sala-I-Martin et al., 2008). Tables 1, 2 and 3 provide the definition, measurement and basic descriptive statistics for each of the variables according to the technology hierarchy.

As already mentioned, the data were drawn by combining several distinct sources of information. Data for Gross Value Added, total hours worked by employees and intermediate inputs were obtained from the database of Groningen Growth and Development Centre, Enerdata-Odyssey database was used to collect data on energy consumption, data on gross fixed

9 Czech Republic, Denmark, Poland, Slovak Republic, Slovenia, Sweden and the United Kingdom

capital formation and capital input files were acquired through OECD Structural Analysis and EU-KLEMS databases respectively. Industry specific deflators were acquired through OECD STAN. The Global Competitiveness Index data were collected from various editions of the Global Competitiveness Report published by the World Economic Forum.

{Insert Table 1 around here}

Very often, the most severe obstruction in the assessment of productive efficiency for a group of DMUs is the lack of a consistent variable reflecting capital stock. To overcome this stumbling block, we draw on the Perpetual Inventory Method (PIM) (see Krautzberger and Wetzel (2012) as an example) to create a consistent measure of capital stock. The initial condition for the capital stock is given by $K_{1999} = \frac{I_{1999}}{\delta + g}$, where g is estimated as the average growth rate in capital investments for the preceding 5 years for each of the examined industries and countries. Given this initial value, the capital stock for each subsequent year is constructed using the formula in Eq.(X):

$$K_{i,t|k} = (1-\delta)K_{i,t-1|k} + I_{i,t|k} \tag{16}$$

where $K_{i,t|k}$ and $I_{i,t|k}$ represent the capital stock and investment of the *i-th* country on the *k-th* industry for the year t respectively, where δ is the depreciation rate which is assumed to be equal to 10% yearly.[10]{Insert Tables 2, 3 around here}

5. Results and Discussion

5.1 Detecting heterogeneity in the evolution patterns of CSIS Technology Gaps

[10] In fact, the estimated capital series did not change in a significant manner when different levels of depreciation rates were considered.

In order to examine the existence of heterogeneous patterns of Technology Gaps evolution we have adopted a finite mixture modelling approach (FMM; McLachlan and Peel, 2005). In contrast to the standard *variable-centered* approaches where we assume homogeneity among the population and we focus on the study of relationships among variables, FMM is considered an *individual-centered* approach and focuses on identifying unobserved subsamples comprised of similar cases which are not known a priori. Of course, such a 'mixture' of different subsamples assumes different underlying distributions which in turn imply population heterogeneity; in other words the sample observations is assumed to arise from a finite number of unobserved subpopulations in the target populations.

Since the number of subgroups existing within our sample are not known a priori and cannot be directly estimated we proceed with estimating a series of ALT mixture models with increasing number of classes and we determine the optimum number of classes by comparing *k*-class model with *(k-1)*-class model iteratively. At this point it should be mentioned that the conventional LR test based on χ^2 statistic is not appropriate strategy for determining the optimum number of classes because the *(k-1)*-class model is a special case of the *k*-class model with one latent class probability being set to zero, thus the difference between the two models does not follow a χ^2 distribution (Muthen, 2004). Therefore, for model comparison we examine a series of fit indices in order to decide the optimal number of latent classes (Nylund et al., 2007).

Table 4 presents the fit indices for three models with *k=1, 2,* and *3*. Specifically, the AIC, BIC ABIC, the Lo-Mendell-Rubin likelihood ratio (LMR LR; Lo et al., 2001) test and the adjusted LMR LR (ALMR LR; (Nylund et al., 2007) are employed in order to decide on the optimal number of classes. With respect to the AIC, BIC and ABIC set of indices, they are log likelihood based and attribute penalties related to model complexity and sample size. Smaller values of information criteria indicate better model fit. In this line, the LMR LR and ALMR LR tests compare a *k*-class with a *(k-1)*-class.

{Insert Table 2 around here}

A statistically significant value of these tests indicate a significant improvement in model fit in the *k*-class model compared to the *(k-1)*-class model. When the LMR LR and ALMR LR tests turn statistically significant, there is no significant improvement in the model from the inclusion of an additional class in the model. One final issue that needs to be addressed is the relative Entropy measure (Dias and Vermunt, 2006) which reflects the uncertainty in classifying observations into latent classes. Values closer to 1.0 indicate more certainty in observations classification. Clark (2010) suggests that a value of 0.80 is high, 0.60 is medium and 0.40 is low entropy. Based on these cutoff criteria we can argue that the classification of EU countries' industrial structures into classes is very close to high and is an additional element that further strengthens the selection of the two-class model.

Turning to this particular case examined, and based on the fit indices presented in Table 4, we can argue that the two-class model is preferable compared to the one-class (i.e. homogeneous evolution of Technology gaps) and the three-class model. Hence, significant heterogeneity in terms of Technology Gaps' evolution patterns is revealed. However, as it has been argued in a previous section of this paper the components of this heterogeneity are still vague and we elaborate further on these below. A graphical representation of the CSIS technology gaps evolution is presented in Figure 2. It becomes apparent that *within the EU economy 'convergence clubs' exist*, that is distinct groups with differential patterns of evolution. Evolution patterns are observed not only within each group but also between groups (Bogliacino and Pianta, 2013; Castellacci et al., 2014).

{Insert Figure 2 around here}

Indeed, a closer examination of the evolution patterns of CSIS Technology gaps reveals that for the period examined, a process of 'divergence' rather than 'catching up' is in operation between groups. According to the estimated means and mean differences between the two groups presented in Table 5, at the beginning of the observation period that is in 2000, the mean estimated difference of the group specific CSIS Technology gaps is 0.190, while the corresponding estimated mean difference at the end of the examined period in 2006 is 0.248.

{Insert Table 3 around here}

On the other hand, within each group a convergence trajectory seems to be in place; the group with the industrial leaders seems to gradually diminishing its mean Technology Gap while the group the industrial followers seems to increase its Technology Gap during the period 2000-2002 and then diminish it for the rest of the time period examined.

An additional element that contributes in determining the heterogeneous patterns of evolution of Technology Gaps is the sectoral composition of EU countries industrial structures. What may be of interest here is the comparison of the role of EU countries' sectoral composition in shaping the evolution patterns of Industrial Leaders and Industrial Followers respectively. More specifically and according to Table 6, Manufacturing and Transportation sector dummy variables in the Industrial Leaders Group are negatively and statistically significant in determining evolution patterns (apart from the influence of Manufacturing sector on the intercept latent variable); whereas Industrial Followers' Group exerts a positive and statistically significant influence on the groups' evolution patterns.

{Insert Table 4 around here}

The above empirical findings indicate that the investigation of the evolution of EU countries industrial structures productive performance is surrounded by multifaceted heterogeneity. It is reflected in EU CSIS Technology Gaps which in turn reveal differential evolution patterns that are also determined by the EU countries' sectoral composition as well as unobserved heterogeneity factors.

5.2 The role of state and path dependence in determining the evolution patterns of CSIS Technology Gaps

The notion of evolution has been inextricably linked with the manifestation of *state* and *path* dependence in dynamic economic processes. Research in this direction is primarily concerned with investigating *whether initial conditions and past states determine the present*. In conceptual terms, state and path dependence reveal one important facet of complexity that rules economics and in general social sciences. In addition, it contributes in arguing that the rule rather than the exception is that structural changes are in fact a gradual processes rather than a radical wave (Dolata, 2013, p. 104). In this line and in the context of the present paper we investigate separately the influence of state and path dependence. The most appealing feature of the employed methodology is that it allows us to investigate the determining roles of State and Path dependence in three ways; firstly, *the pure effect of state dependence* is modeled through the covariance of the latent variable approximating the mean structure of the initial state (α_i) of each latent class k with the initial conditions of each observation; secondly, *the pure effect of path-dependence* is modeled by the time varying autoregressive parameter $\rho_{t,t-1}$ for each of the identified groups; furthermore, we also investigate the joint effect of growth patterns namely the interrelationship between the initial state (α_i) and the rate of growth (β_i) in shaping the CSIS technology gaps evolution.

Table 6 presents the estimated covariances between the latent growth parameters and initial conditions, while Table 7 presents the estimated autoregressive parameters $\rho_{t,t-1}$.

{Insert Table 6 around here}

{Insert Table 7 around here}

With respect to the Industrial Leaders Group the *pure effect of state dependence* is negative and statistically significant. Hence, for the *i*-th industry classified in the Industrial Leaders group, the class specific mean initial state with the industry specific initial conditions exert a negative influence on the evolution of its Technology Gap. In other words, pure state dependence is an important factor in determining the evolution of Technology Gaps in the Industrial Leaders Group. The initial conditions of this group act as an advantage that determines positively their entire subsequent growth process. On the other hand, the pure state dependence effect seems not to be a determining factor in the Industrial Followers group. Moving forward, we examine the *pure effect of path dependence* on the evolution patterns of both latent groups. Regarding the Industrial Leaders group a persistent negative and statistically significant effect of path dependence is identified. It is interesting to note that path dependence patterns are decreasing functions of time. On the other hand, even though path dependence has been identified for three consecutive time periods, at the beginning of the period the industrial followers group did not exhibit a path dependent effect statistically different from zero. It should be noted however that comparing the path dependent effects across groups it becomes evident that the Industrial Leaders Group are both more capable and faster in reducing their Technology Gaps compared to the Industrial Followers Group.

Last but not least, the joint effects of path and state dependence as they are presented in Table 6 indicate similar patterns for both groups of CSIS Technology gaps evolution patterns. In particular, the joint effect of path and state dependence manifests with the covariance between the rate of growth of CSIS Technology Gaps and class specific initial state of Technology Gap evolution which is negative and statistically significant for both groups, indicating that a high level the initial state of an *i*-th industry would exert a negative influence in the rate of growth of its technology gap. *Put differently a high initial Technology Gap will result in a weakened rate of growth, and thus a weakened catching up rate*.

5.3. The relationship between Competitiveness and Evolution of CSIS Technology Gaps

The last remaining hypothesis to be examined is whether the differential patterns of Technology Gap evolution determine at the end of the period the EU countries' Competitiveness. The logistic regression estimation results are presented in figuratively below for reasons of simplicity.

{Insert Figure 3 around here}

The industries classified at the Industrial Leaders Group have 66.2% probability of finding themselves above the median of the Global Competitive Index (GCI) in 2006 while industries classified at the Industrial Followers Group present only 55.5% probability of being above median of the GCI at the end of the observation period. These empirical findings suggest that those industries with low levels of technology gap at the beginning of the observation period and stronger path dependence are more likely to secure their competitive position compared to those industries that belong to the Industrial Followers Group.

6. Conclusions

With this paper we investigate the role of evolution patterns of productive performance of EU countries industrial structures on their competitiveness, by introducing a rather novel methodology *which accounts for more than one components of evolution* and employing the concept of technology gaps, in a multidimensional heterogeneity framework. More specifically, the notion of technology gaps reflects the *latent* influence of absorptive capacity, strategic orientation as well as of the knowledge spillovers *within* and *between* EU countries on Country Specific Industrial Structure (CSIS) productive performance.

We have argued on the *complexity* surrounding the investigation of evolution patterns of CSIS Technology Gaps. Such a complexity is highlighted when we consider the hypothesis that the evolution patterns of CSIS technology gaps are heterogeneous and “convergence clubs” exist within the EU. In addition, we have also accounted for the role of sectroral composition in determining the evolution patterns of CSIS Technology Gaps. Furthermore, we have modeled the evolution patterns of CSIS Technology Gaps accounting for both state and path dependence.

Exploiting a unique dataset of 17 European Countries and 13 industries belonging to the Manufacturing and Transport sectors for the period 2000-2006, we firstly estimated CSIS technology gaps arising in a metafrontier context. We then estimated an Autoregressive Latent Trajectory mixture model in order to estimate the evolution patterns of CSIS technology gaps. At the same time we estimated the effect of such evolution patterns on EU countries' competitiveness. Overall the empirical results reveal convergence processes within both the technology leaders and the followers groups and divergence patterns across the two heterogeneous classes. These phenomena are assigned to path and state dependence as well as to technology heterogeneity between European Sectors which although is affected from the flows between the country remains significant. Finally both classes are more likely to improve their competitive position at the end of the observation period however; the industries which are assigned to the Leaders Group face higher probability in improving their competitive status compared to those assigned at the Followers Group.

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Appendix I

Table 1. Variables, units of measurement and sources of information

Variable	Units of measurement	Source
Output (Y)	million euros	GGDC
Capital (K)	million euros	OECD STAN, EUKLEMS
Labor (L)	million hours worked by employees	GGDC
Intermediate inputs (M)	million euros	GGDC
Energy consumption (E)	million tons of oil equivalent	Enerdata - Odyssey
Global Competitiveness Index	pure number	World Economic Forum
All the values are in constant 2000 prices using industry specific deflators.		

Table 2: Descriptive Statistics of the variables per country with respect to the Meta-Frontier for 2000-2006

Country	Y	K	L	E	M
Austria	3,749	20,426	107.975	1.153	5,786
	(3,732)	(22,744)	(114.683)	(1.859)	(3,953)
Belgium	4,320	19,461	99.815	1.647	11,439
	(3,234)	(14,373)	(77.534)	(2.346)	(8,060)
Czech Rep.	1,614	10,976	189.263	1.080	4,491
	(1,231)	(23,844)	(169.705)	(1.482)	(4.052)
Denmark	2,401	9,159	65.533	.589	4,746
	(1,971)	(6,941)	(62.069)	(1.016)	(4,417)
Finland	2,555	9,159	64.115	1.383	4,357
	(2,173)	6,941)	(59.790)	(2.225)	(3,813)
France	19,716	63,842	558.171	6.659	42,524
	(17,284)	(69,373)	(580.158)	(11.052)	(35,394)
Germany	31,995	96,897	928.138	9.296	60,073
	(24,969)	(98,318)	(812.794)	(14.818)	(51,865)
Greece	2,055	9,796	101.646	.892	2,665
	(2,678)	(10,279)	(115.950)	(1.505)	(3,218)
Ireland	2,664	9,468	54.229	.541	4,316
	(3,563)	(9,462)	(76.510)	(.972)	(4,992)
Italy	18,739	103,214	569.381	6.404	41,557
	(14,874)	(96,987)	(476.815)	(10.194)	(26,641)
Netherlands	6,033	30,423	161.328	2.225	12,643
	(5,169)	(30,802)	(158.568)	(2.629)	(11,723)
Poland	3,092	24,270	348.803	1.981	7,091
	(3,099)	(28,651)	(316.457)	(2.795)	(6,287)
Slovak Rep.	572.215	131.896	62.433	.464	1,560
	(509.262)	(207.664)	(55.152)	(.652)	(1,851)
Slovenia	1.612	15.147	30.837	.235	3.807
	(1.249)	(16.361)	(26.980)	(.344)	(2.911)
Spain	12,423	87,914	574.034	4.686	26,571
	(13,799)	(60,901)	(818.315)	(7.440)	(24,214)
Sweden	4,343	20,976	120.009	1.627	7,888
	(2,981)	(22,553)	(102.452)	(2.258)	(5,384)
United	22,006	102,949	638,169	6.502	37,581
Kingdom	(18,635)	(75,459)	(566.057)	(11.035)	(31,475)
	8,137	**36,336**	**274.934**	**2.786**	**16,194**
TOTAL	**(13,651)**	**(59,419)**	**(460.343)**	**(6.782)**	**(26,434)**

Table 3: Descriptive Statistics of the variables employed in ALT mixture model

Technology Gaps	**Mean (St. Dev.)**	**Binary Variables**	**Frequencies**
TG_{2000}	0.436 (0.207)	$D_{Manufacturing}$	1= 61.53% 0= 38.47%
TG_{2002}	0.482 (0.211)	$D_{Tramsportation}$	1= 30.76% 0= 69.24%
TG_{2004}	0.453 (0.215)	$D_{Construction}$	*Reference Group*
TG_{2006}	0.420 (0.205)	GCI_{2006}	1= 47.5% 0=52.5%
		No. of observations	221

Table 4. Comparison of different ALT mixture models

Model	AIC	BIC	ABIC	LMR LR test P-value	ALMR LR test P-value	Entropy
1-class	-1000.833	-932.870	-996.251	-	-	1.000
2-class	**-1074.490**	**-952.156**	**-1066.241**	**0.0759**	**0.0785**	**0.780**
3-class	-1002.095	-825.391	-990.181	0.3415	0.3425	0.696

Table 5. Estimated means and mean differences between the two latent classes

Estimated Means for Industrial Leaders Group					
Intercept	Slope	TG2000	TG2002	TG2004	TG2006
0.331	0.306	0.331	0.334	0.310	0.284
Estimated Means for Industrial Followers Group					
Intercept	Slope	TG2000	TG2002	TG2004	TG2006
0.521	0.361	0.521	0.612	0.573	0.532
Mean Differences					
0.190***	0.055**	0.190***	0.278***	0.263***	0.248***
(0.021)	(0.040)	(0.024)	(0.020)	(0.022)	(0.021)

Table 6. Empirical results on the role of sectoral composition in determining the evolution patterns of EU countries' industrial structures Technology gaps

	Industrial Leaders Group		Industrial Followers Group	
	Intercept	Slope	Intercept	Slope
DMANUF	-0.072	-0.309***	0.389***	0.298***
	(0.066)	(0.120)	(0.025)	(0.084)
DTANSP	-0.202***	-0.285***	0.371***	0.360***
	(0.076)	(0.116)	(0.033)	(0.086)

Table 7. Class specific co-variances estimation with respect to initial conditions, initial state and rate of growth of Technology Gaps

	Industrial Leaders Group	Industrial Followers Group
$COV\left(\alpha_i, \varepsilon_{iTG2000}\right)$	-0.009*	-0.005
	(0.005)	(0.004)
$COV\left(\alpha_i, \beta_i\right)$	-0.021***	-0.021***
	(0.008)	(0.008)

Table 8. Empirical results of the Autoregressive part of the model regarding the existence of path dependence in determining the evolution patterns of EU countries' industrial structures Technology gaps

	Industrial Leaders Group	Industrial Followers Group
$\rho_{TG_{2002,2000}}$	-0.269***	-0.034
	(0.041)	(0.052)
$\rho_{TG_{2004,2002}}$	-0.615***	-0.270***
	(0.063)	(0.093)
$\rho_{TG_{2004,2006}}$	-0.920***	-0.470***
	(0.096)	(0.124)

Figure 1. Framing the influence of multilevel technological heterogeneity and state and path-dependence with the evolution patters of Technology gaps and its impact on EU countries' competitiveness

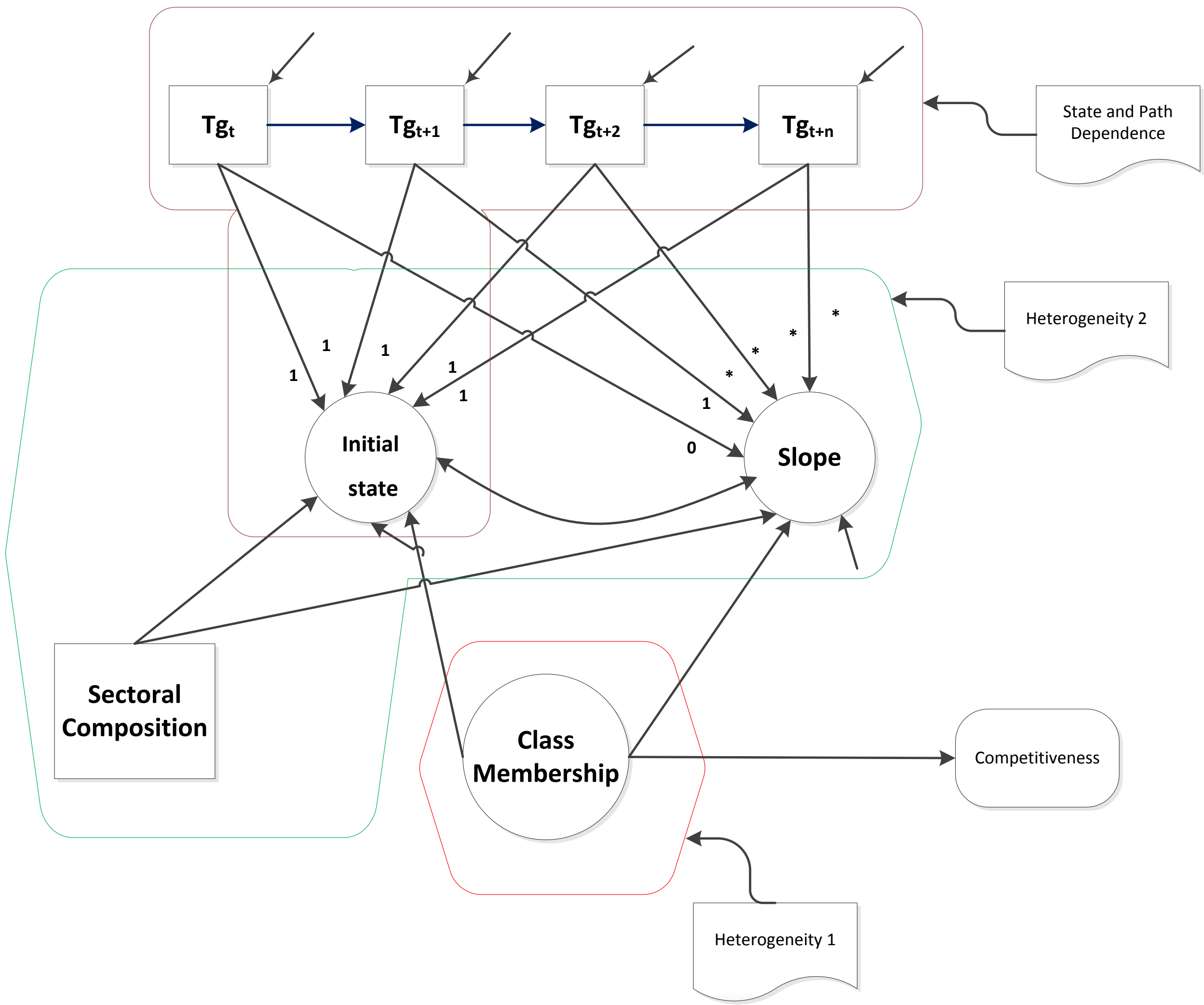


Figure 2. Class specific evolution patterns of Technology Gaps of EU countries' industrial structures

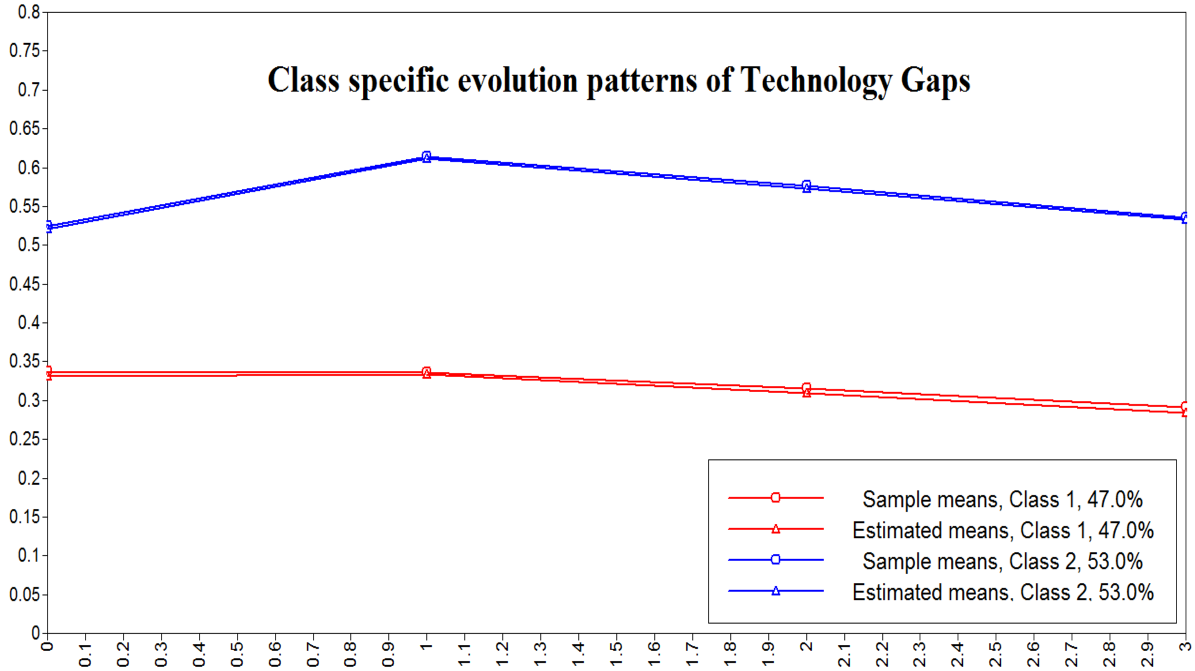
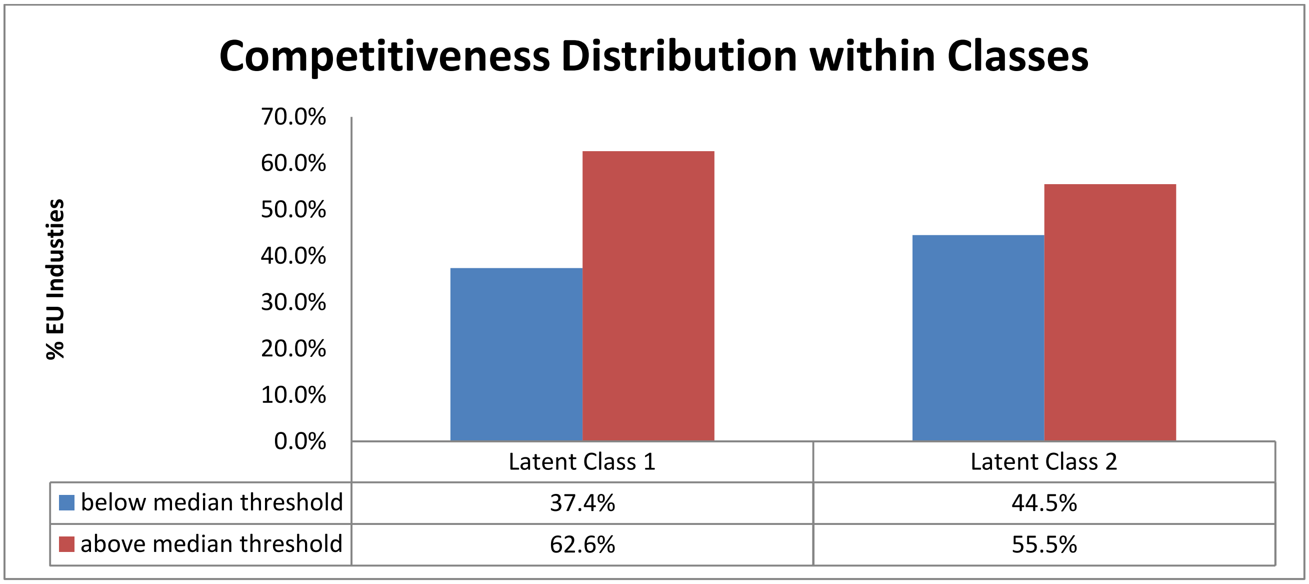


Figure 3. Distribution of competitiveness of EU industries at the end of the observation period depending on class membership



Appendix II

Table I. Classification of EU countries industrial structures in Groups based on their Technology Gaps evolution patterns

Latent Group 1		Latent Group 2	
Austria	Basic Metals Metals Food and Beverages Other non-metallic materials Pulp Textiles Supporting and auxiliary transport activities Water Transport	Austria	Air Transport Chemicals Construction Land Transport Transport Equipment Wood
Belgium	Construction Water Transport	Belgium	Air Transport Basic Metals Chemicals Food and Beverages Land Transport Other non-metallic materials Pulp Supporting and auxiliary transport activities Textiles Transport Equipment Wood
Czech	Chemicals Construction Land Transport Water Transport	Czech	Air Transport Basic Metals Food and Beverages Other non-metallic materials Pulp Supporting and auxiliary transport activities Textiles Transport Equipment Wood
Denmark	Basic Metals Construction Pulp Supporting and auxiliary transport activities Transport Equipment	Denmark	Air Transport Chemicals Food and Beverages Land Transport Other non-metallic materials Textiles Water Transport

			Wood
Finland	Construction Food and Beverages Land Transport Pulp Supporting and auxiliary transport activities Water Transport Wood	Finland	Air Transport Basic Metals Chemicals Other non-metallic materials Textiles Transport Equipment
France	Basic Metals Chemicals Food and Beverages Land Transport Supporting and auxiliary transport activities Transport Equipment Wood	France	Air Transport Construction Other non-metallic materials Pulp Textiles Water Transport
Germany	Basic Metals Chemicals Food and Beverages Land Transport Other non-metallic materials Pulp Supporting and auxiliary transport activities Transport Equipment Water Transport Wood	Germany	Air Transport Construction Textiles
Greece	Food and Beverages Land Transport Other non-metallic materials Pulp Supporting and auxiliary transport activities Transport Equipment Water Transport	Greece	Air Transport Basic Metals Chemicals Construction Textiles Wood
Ireland	Air Transport Basic Metals Chemicals Food and Beverages Pulp Supporting and auxiliary transport activities	Ireland	Construction Land Transport Other non-metallic materials Wood

	Textiles Transport Equipment Water Transport		
Italy	Basic Metals Land Transport Supporting and auxiliary transport activities	Italy	Air Transport Chemicals Construction Food and Beverages Other non-metallic materials Pulp Textiles Transport Equipment Water Transport Wood
Netherlands	Water Transport Air Transport Basic Metals Chemicals Food and Beverages	Netherlands	Basic Metals Chemicals Food and Beverages Supporting and auxiliary transport activities Textiles Transport Equipment Water Transport Wood
Poland	Land Transport Other non-metallic materials Pulp	Poland	Air Transport Basic Metals Chemicals Food and Beverages Land Transport Other non-metallic materials Pulp Textiles Transport Equipment Wood
Slovakia	Supporting and auxiliary transport activities Textiles Water Transport Wood Air Transport Construction Food and Beverages Textiles Transport Equipment	Slovakia	Construction Transport Equipment

	Water Transport Wood		
Slovenia	Land Transport Supporting and auxiliary transport activities Water Transport Air Transport Food and Beverages Pulp Water Transport	Slovenia	Basic Metals Chemicals Land Transport Other non-metallic materials Pulp Supporting and auxiliary transport activities
Spain	Wood Basic Metals Food and Beverages	Spain	Air Transport Basic Metals Chemicals Construction Food and Beverages Other non-metallic materials Pulp Textiles Transport Equipment Wood
Sweden	Land Transport Pulp Supporting and auxiliary transport activities Water Transport	Sweden	Basic Metals Chemicals Construction Land Transport Other non-metallic materials Supporting and auxiliary transport activities Textiles Transport Equipment
UK	Food and Beverages Pulp Basic Metals Land Transport Water Transport Supporting and auxiliary transport activities	UK	Air Transport Chemicals Construction Other non-metallic materials Textiles Transport Equipment Wood