The heterogeneity of European Higher Education Institutions. A configurational approach

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Summary

To investigate the heterogeneity of Higher Education Institutions (HEI), this paper builds on the literature on organizational typologies and on HEI diversity to construct a conceptual model that is tested on a large sample of European HEIs. Results show that heterogeneity can be represented along two main axes, i.e. research vs education orientation and the extent of subject specialization. The first axis associated with the distinction between universities and colleges, but there is a significant extent of blending with intermediate categories emerging such as 'new' universities and research colleges. On the subject specialization side, the model moves beyond the distinction between generalist and specialists to identify two distinctive groups of specialists, i.e. technical universities and universities specialized in a social sciences and humanities. We further envisage deepening the association of classes with underlying HIE characteristics such as their HEI identity and/or institutional mission.

1 Introduction

It is well-known that the European higher education landscape is characterized by a high level of heterogeneity, with Higher Education Institutions (HEIs) characterized by different institutional mandates and missions, as well as different mixes of activities (Huisman et al., 2015). While only few hundreds HEIs are competing globally for international excellence (Hazelkorn, 2009), most HEIs are mainly oriented to serve educational needs and keep strong rootings with their local communities (Paradeise and Thoenig, 2013). Heterogeneity has been generated by different processes, including the internal differentiation of academic disciplines (Clark, B., 1978), national policies creating second-tier HEIs (Kyvik, 2006) and different demands by societal stakeholders (Meek, 2000).

Our understanding of heterogeneity remains however limited. Most studies focused on the (legally defined) distinction between universities and non-university HEIs (Kyvik and Lepori, 2010) and on isomorphic tendencies between these two types of institutions (Meek et al., 1996, van Vught, F., 1996). Other studies measured diversity at the level of national systems without looking to individual institutions (Birnbaum, 1983, Huisman et al., 2015). The few micro-level studies have been largely descriptive (Daraio et al., 2011) or focused on individual types of HEIs (Teixeira et al., 2014), respectively on individual countries (de la Torre, Eva M et al., 2018,Rossi, 2010).

In order to advance our understanding of HEI heterogeneity, this paper introduces conceptual, methodological and data advances. First, we build on the literature on organizational typologies (Doty et al., 1993) to develop an explicit framework to represent heterogeneity, while drawing on the higher education literature for the identification of the relevant dimensions for characterization (Huisman et al., 2015). Second, we introduce latent class clustering as a suitable statistical tool in order to identify HEI classes from the data (Muthén, 2004; Vermunt and Magidson, 2002). Third, we exploit a rich set of data provided by an enriched version of the European Tertiary Education Register in order to analyze heterogeneity on a large sample of more than 2,000 HEIs in a large number of European countries (Lepori, Benedetto et al., 2017).

2 Modeling HEI heterogeneity

A configurational approach on heterogeneity rests on the idea that observable organizational characteristics are not randomly distributed, but there are systematic interdependencies between some attributes (Fiss, 2011). These might be associated to technological interdependencies, but also to (not directly observable) dimensions like the mission or identity of an organization. In the case of HEIs, we might argue that research and educational activities are interdependent, because of potential complementarities and trade-offs in terms of resources, but also of attention by the academic staff and institutional management. Accordingly, a configurational approach goes beyond a simple classification and might provide inference on some underlying characteristics of organizations like their technology, identity and mission (Musselin, 2007; Whitley, 2008).

Such interdependencies can be represented conceptually in terms of 'ideal types', "each of them representing a unique combination of the organizational attributes that are believed to determine the relevant outcomes" (Doty et al., 1993), but are also observed empirically by grouping observations through methods like cluster analysis (Drazin and Van de Ven, Andrew H, 1985). The two approaches are in fact complementary (Meyer et al., 1993): conceptual design may suggests relevant dimensions for classification, which are tested empirically; eventually, classes derived from the data are then reinterpreted in terms of ideal-types to lead to a more robust conceptual model.

As of HEIs, the literature on institutional diversity in Higher Education (Birnbaum, 1983; Huisman et al., 2015) suggests two key dimensions of characterization:

First, the *activity profile* in terms of three main activities and outputs, i.e. education, research and third-mission. While traditionally it has been considered that education and research are closely associated in universities (Clark, Burton R., 1995), the establishment of HEIs without an explicit research mandate and differentiation in the HEI landscape imply that the relationships between the two activities might vary by HEI types. Moreover, third-mission has become an important dimension of HEI activities, up to the definition of Entrepreneurial HEIs as a distinct class of institutions (Etzkowitz, 2004).

An important factor associated with activity profiles have been policies aimed at institutional differentiation, with the creation of a 'second' sector of higher education including HEIs mostly oriented towards professional education (Meek et al., 1996); over time, these institutions attempted to develop some research activities (Lepori, Benedetto, 2009), but the extent of similarities and differences with universities remains heavily debated (Huisman et al., 2015).

The *subject scope*, i.e. the diversity of the subject domains covered by HEI activities (Clark, Burton R., 1995). Subject specialization is relevant for market positioning: HEIs that are active in many subjects cover a broader range of educational demands and tend to have larger enrolment, while specialized HEIs might leverage their distinctive identity to attract students (Lepori, B. et al., 2010). The literature usually distinguishes between the *generalist HEI* covering most subject domains, and the *specialist HEI,* whose identity is defined by the subject ("technical school", "Art school", etc.; Van Vught, Frans, 2009).

Further, we include organizational size as measured by the number of staff given that it strongly impacts on activities and is a good proxy for the ability of HEIs to acquire resources (Huisman et al., 2015).

Finally, we take into account two regulatory (exogenous) characteristics that are likely to influence the HEI profile and classification, i.e. the legal status pf the HEI (public vs. private; Teixeira et al., 2014) and the research mandate, as represented by the legal right to award a PhD (Kyvik and Lepori, 2010).

3 Data, variables and methods

3.1 Data

The analysis is based on an enriched version of the European Tertiary Education Register (ETER), which provides data at the level of individual HEIs, including organizational descriptors, number of students and degrees, number of staff, expenditures and revenues. The 2014 edition of ETER includes 2,830 HEIs in 37 European countries and provides an extensive coverage of higher education (almost 100% in terms of students; Lepori, Benedetto et al., 2017). Five countries have been dropped because of too many missing data (Albania, Denmark, Estonia, Montenegro and Romania), Within the RISIS project (risis.eu), ETER has been enriched with data on scientific publications derived from the Web of Science version at the University of Leiden (Waltman, Calero-Medina, Kosten, et al 2012), on European projects from the EUPRO database (Roediger-Schluga and Barber, 2008) and on patents from the PATSTAT version at IFRIS in Paris (Laurens et al., 2015). Non identified cases have been attributed a null score.

While comparability problems of HEI data across countries are well-known (Bonaccorsi et al., 2007), ETER made an effort to achieve standardization: definitions were codified, relying largely on official statistics; systematic data checks were performed and deviant cases were cross-checked with national statistical authorities; finally, problem cases have been identified and flagged. Comparability problems are unlikely to bias an analysis based on a large number of cases.

3.2 Variables

The selection of variables draws on our conceptual framework (Table 1). In order to reduce collinearity, we focus on ratios or intensity indicators (normalized by staff), while we log transform the only volume variable, i.e. academic staff, since its distribution is nearly lognormal.

As of education, we resort to the number of students at the diploma, bachelor and master level; we further add a measure of the orientation of the education towards the master level, as it is an important indicator characterizing the educational profile. As of research, we resort to an indicator combining PhD graduates, scientific publications and European projects, since the three measures are highly correlated. We also introduce an indicator of international visibility as the number of Web of Science citations per staff. Finally, we use the number of patent as an indicator of third-mission, since other measures (like private funds) are not available for most of the sample.

In terms of subject mix, we include an indicator of subject concentration across educational domains and two indicators of the direction of specialization, i.e. the share of students in social sciences and humanities and the share in natural sciences and engineering.

We finally include dummies for legal status and research mission, measured through the status of awarding a PhD.

Data availability is quite good for all variables, the main limitation being a number of missing data for staff and for the subject composition. We purposefully refrained using financial data since their availability in ETER is much lower. While LCA models can use observations even if some variables are missing, we drop all cases for which staff data are missing, as this implies that most other variables will also be missing. Our final sample therefore includes 2243 observations in 30 European countries, with the largest numbers in Germany (385 HEIs), Poland (282 HEIs), Italy (215 HEIs), Turkey (181 HEIs), UK (160 HEIs) and France (127 HEIs). These six countries alone account for 60% of the observations.

Table 1. Dimensions and variables

Dimension	Variable	Definition and remarks	Valid cases	Completeness
Institutional size	Ln(Academic staff in Full-Time Equivalent)	Educational and research personnel, including PhD students.	2241	100%
Educational activities	Education intensity	Number of diploma, bachelor and master students divided by academic staff.	2237	100%
	masterorientation	Number of master students divided by the number of diploma, bachelor and master students.	2228	99%
Research activities	Research intensity	Average of the number of PhD graduates, of scientific publications and of European projects (each rescaled between 0 and 1) divided by the academic staff	2241	100%
	Citations per staff	Total normalized citation score divided by the academic staff.	2241	100%
Third mission	Patent intensity	Number of patents in 2010-2013 divided by academic staff.	2241	100%
Subject scope	Subject concentration	Herfindahl index of the distribution of the bachelor and master students by the ten fields of educational statistics. This index is 1 if all students are in a single field.	2033	91%
	Share students in social sciences and humanities	Share of bachelor and master students in the corresponding fields.	2014	90%
	Share students in natural sciences and engineering	Share of bachelor and master students in natural sciences, ICT and engineering.	2014	90%
Regulatory characteristics	Public vs. private	Dummy, 0 if the institution is under public control or is mostly financed by the state, 1 if it is private.	2243	100%
	Research mandate	Dummy, 1 if the HEI has the legel right to award the PhD, 0 otherwise.	2232	100%

Table 2 shows that most correlations between variables are below 0.5 except those between staff and subject concentration, between the two research variables and between shares of students in social sciences and humanities and in natural sciences.

Table 2. Correlation table

	lnstaff	education_intensity	masterorientation	research_intensity	citationsstaff	patentintensity	Herfindahl57	share_ssh	natsci
lnstaff	1.000								
education_intensity	-0.238	1.000							
masterorientation	0.104	-0.182	1.000						
research_intensity	0.458	-0.054	0.317	1.000					
citationsstaff	0.450	-0.064	0.267	0.874	1.000				
patentintensity	0.279	-0.077	0.115	0.250	0.223	1.000			
Herfindahl57	-0.648	-0.011	0.187	-0.272	-0.265	-0.134	1.000		
share_ssh	-0.300	0.038	0.001	-0.243	-0.221	-0.266	0.285	1.000	
natsci	0.299	-0.030	0.079	0.253	0.198	0.348	-0.274	-0.743	1.000

3.3 Constructing classes

To attribute HEIs to classes, we use latent class clustering (Muthén, 2004; Vermunt and Magidson, 2002). This class of models fits the distribution of a set of observed variables conditional to the observations belonging to non-observed (latent) classes; compared with conventional clustering methods, latent-class clustering presents the advantage of being model-based (hence it can incorporate prior assumptions on classes and statistical distributions) and has been shown to provide much better results (Magidson and Vermunt, 2002).

More precisely, given a sample of HEIs, the model represents the observed characteristics as the mixture of Gaussian distributions conditional to the probability of belonging to some latent class

$$\mathrm{f}(\boldsymbol{y}) = \sum_{ij} \pi_i f_i(\boldsymbol{y})$$

where $\boldsymbol{y}$ is the set of observed variables as in Table 1.

The probability of belonging to a class is made contingent to a set of exogenous variables

$$\pi_i = f_i(\mathbf{x}) = \frac{\exp(\gamma_i)}{\sum_1^g \exp(\gamma_i)}$$

Class 1 is the baseline for which $\gamma_i = 0$ and $\exp(\gamma_i) = 1$, so that $\sum_i \pi_i = 1$. Since in our model, the probability of belonging to a class is contingent on two exogenous regulatory variables, i.e. the legal status and the research mandate:

$$\gamma_i = \theta_i + \mu_i\,(legal\ status) + \vartheta_i\,(research\ mandate)$$

Where θ_i is a normally distributed random variable. The interpretation is that regulatory variables will increase or decrease (depending on the coefficients) the probability of an HEI belonging to a class; the strength of the association between regulatory characteristics and classes is however determined by the model based on the observed data.

The baseline model treats the observed variables as conditionally independent to the observations belonging to a class; it is however possible to specify a covariance matrix between variables to take into account remaining dependencies.

The model computes the distribution functions and the posterior probability for each HEI to belong to a class and searches iteratively for the solution maximizing the model fit. It must be run with a pre-specified number of classes, but the optimal number can be selected ex-post by comparing statistics such as the Akaike Information Criterion (Nylund et al., 2007). Given its sensitivity to initial conditions, each model has been run with 15 random draws and the best solution has been selected.

The analysis shows that the fit statistics improves up to five classes and then goes down, as the better fit does not compensate for the increasing complexity of the model. We therefore selected the 6-class model as our reference model. On the five-class model, we additionally tested different specifications of the model by introducing covariance matrices between the most correlated variables; the model fit does not however improve. We also resort to the second-best model, i.e. the nine class model, to see whether a more fine-grained model produces different results.

Table 3. Fit statistics

Class	Obs	ll	df	AIC	BIC
gsem2	2’230	50916.02	34	-101764	-101570
gsem4	2’230	54531.88	55	-108954	-108640
gsem5	2’230	75599.96	90	-151020	-150506
gsem6	2’230	57564.01	100	-114928	-114357
gsem7	2’230	59903.26	109	-119589	-118966
gsem8	2’230	58625.57	111	-117029	-116395
gsem9	2’230	71916.64	158	-143517	-142615
gsem10	2’230	67528.08	155	-134746	-133861

To interpret results, we finally assign each case to the class with the highest probability and we compute descriptive statistics by class.

4 Results

For the five-class model, Table 4 displays the posterior probabilities for an HEI to belong to a class for each combination of the regulatory characteristics, while Table 5 provides descriptive statistics as a starting point to characterize classes, based on the assignment of cases to the class with the highest score.

Posterior probabilities display clear associations between regulatory characteristics and classes, with most public colleges (non-PhD awarding) and private HEIs concentrated in class 1 and most universities concentrated in classes 2 and 3. Looking by class, classes 2, 3 and 4 are mostly composed by universities (public, also private for class 3), while classes 1 and 5 by colleges and by private institutions (for class 1). At the same time, the association between classes and regulatory characteristics is not tight, for example a sizeable number of universities are in the 'colleges' class 1. The nature of these cases deserves a closer investigation.

Table 4. Posterior relative probabilities to belong to each class

Regulatory characteristics	N. cases	Class 1	Class 2	Class 3	Class 4	Class 5
Public, PhD	997	0.12	0.40	0.28	0.16	*0.04*
Public, no PhD	581	0.70	0.03	*0.10*	0.06	0.11
Private, PhD	446	0.46	0.07	*0.40*	0.05	0.02
Private, no PhD	208	0.92	0.00	*0.05*	0.01	0.02

A simple characterization of classes based on their medians displays some clear differences and distinguishing features. Classes 2 and 4 are distinguished by high research and patent intensity, class 2 is composed by generalist universities, while class 4 by institutions focused on natural and technical sciences, with a very high patent intensity. Classes 3 has medium research intensity, institutions in this class are mostly universities and specialized in social sciences and humanities, while class 5 is composed mostly by colleges, however with some research and patenting activity. Class 1, the class including most observations, is composed by colleges (and some private PhD-awarding institutions), mostly specialized in social sciences and humanities.

Table 5. Basic statistics for classes with characterizing dimensions highlighted

Class		N	Regulatory characteristics				Median characterizing variables								
			PhD		Legal										
			no	yes	Public	private	academic staff	education intensity	masterorientation	research intensity	citationsstaff	patentintensity	HF students	students SSH	students natsci
1	Specialised colleges (SSH)	1'033	819	214	527	506	52.0	18.5	0.14	0.000000	0.000	-	0.64	0.93	0.00
2	Research universities	436	15	421	421	15	1092.0	16.0	0.32	0.000059	0.269	0.018	0.18	0.57	0.26
3	Social sciences universities	440	79	361	335	105	257.4	21.0	0.23	0.000014	0.003	-	0.38	0.82	0.09
4	Technical universities	206	36	170	193	13	415.0	14.8	0.40	0.000059	0.194	0.041	0.44	0.16	0.71
5	Generalist colleges and universities	115	76	39	102	13	387.4	21.5	0.15	0.000004	0.000	0.005	0.29	0.44	0.40

For comparison, the 9-class model produces rather similar results with more than ¾ of the HEIs in the same classes; the research universities class is split into two subclasses, while the three additional classes include research centers, HEIs with high education intensity such as distance education institutions and a group of social sciences universities with high research intensity. We consider that the additional complexity is not justified by the higher degree of detail.

4.1 Characterizing classes

As a next step, we provide more fine-grained view of the classes and of their distinctiveness (and overlap) through further descriptive statistics and looking to the HEIs belonging to each class. As shown by Figure 1, almost all research activity is concentrated in the three university classes, whereas social sciences universities have lower publication output due also to the limited coverage of the Web of Science in their domains. These three classes are clearly distinguished by their subject specialization (Figure 2).

Figure 1. Number of publications and pf PhD students by class

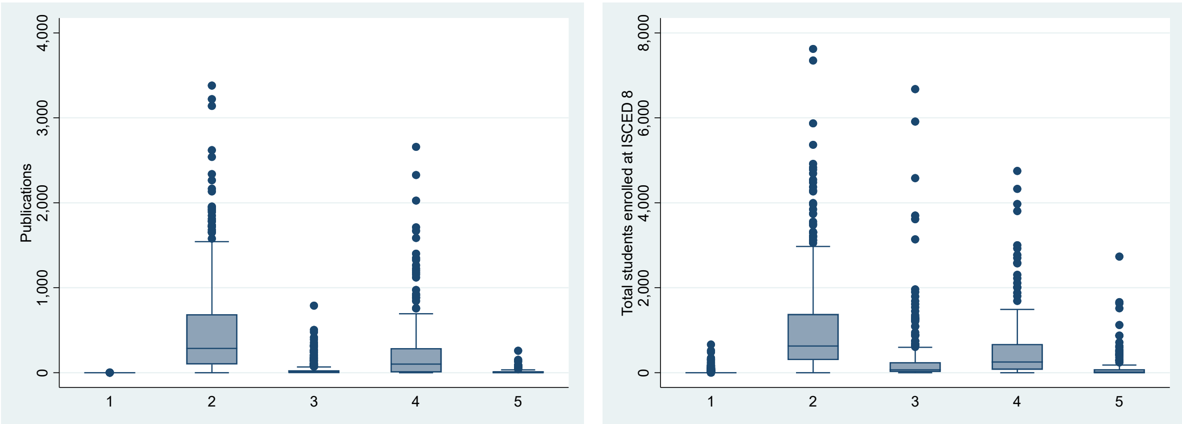
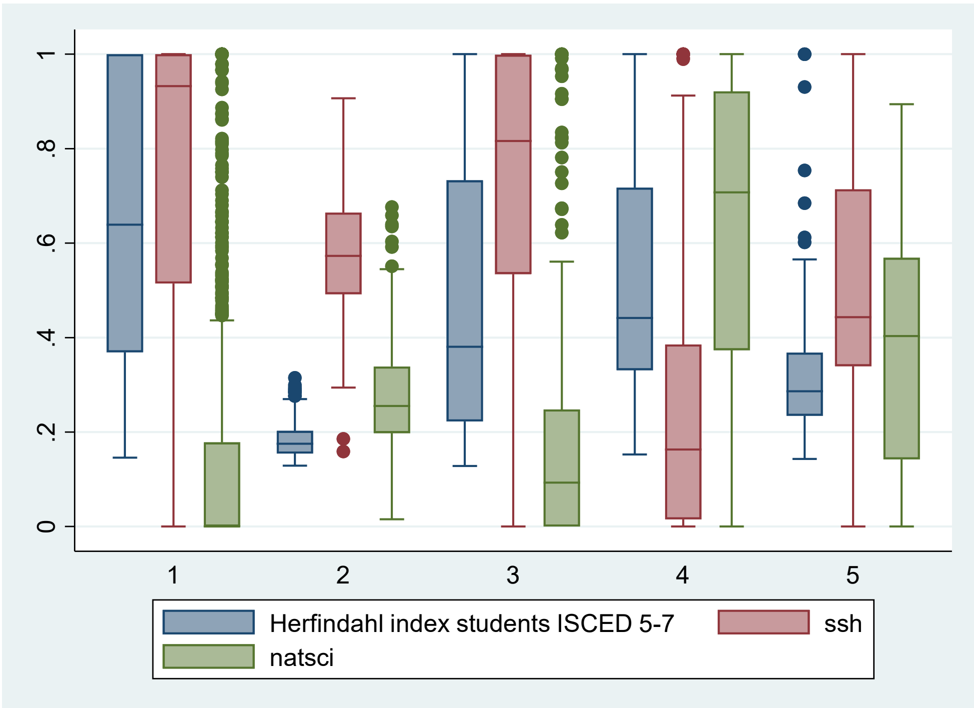


Figure 2. Subject specialization by class

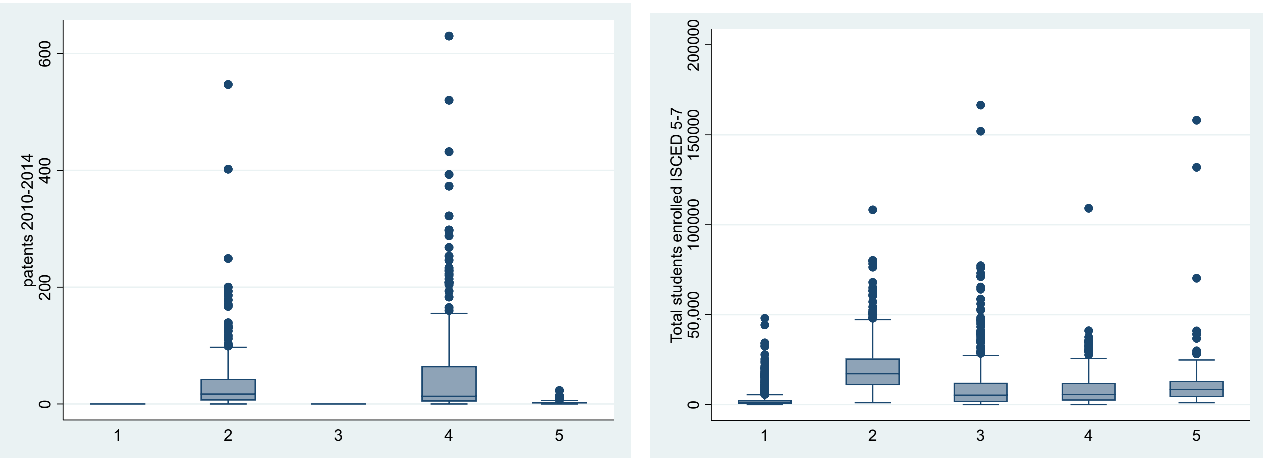


Class 2 includes nearly all generalist universities ranging from all top-ranked international universities, like Oxford and Cambridge, to middle-size European universities such as Augsburg or Brighton; this group also includes very few colleges with some research activities (particularly European projects and patents), such as some Swiss Universities of Applied Sciences. As suggested by the nine-class model, it would be in principle possible to split further this group based on the level of research intensity.

Class 4 includes the remaining top-ranked universities in Europe that are focused on natural and technical sciences, such as ETH Zurich, Imperial College and TU Munich, as well as middle-size technical schools and some medical schools. While these universities have a research intensity similar to group 2, they are clearly distinguished by the much larger patent activity.

Finally, class 3 includes universities with a specialization in social sciences and humanities, such as Tilburg, Trier or Salzburg. These universities are smaller in terms of academic staff, but fairly large in terms of enrolments (see Figure 3). This group also includes also a sizeable number of private universities and colleges, which are however distinguished from group 5 for their subject specialization.

Figure 3. Patents and undergraduate students



Class 5 includes HEIs (mostly colleges) characterized by no or very low research activity, but by large student enrolments – this is the second largest class by student numbers. It includes some of the largest colleges, such as Inholland in the Netherlands and Cologne in Germany, distance education universities.

Finally, class 1 includes most colleges in our sample: most of them are very small and highly specialized, such as schools of music, art or theology, but also includes some of the larger colleges such as in the Netherlands. This groups also includes a number of PhD awarding institutions, such as music and theological schools in Germany and some of the ‘new’ universities in the UK, showing how the statistical approach is able to take into account these special cases.

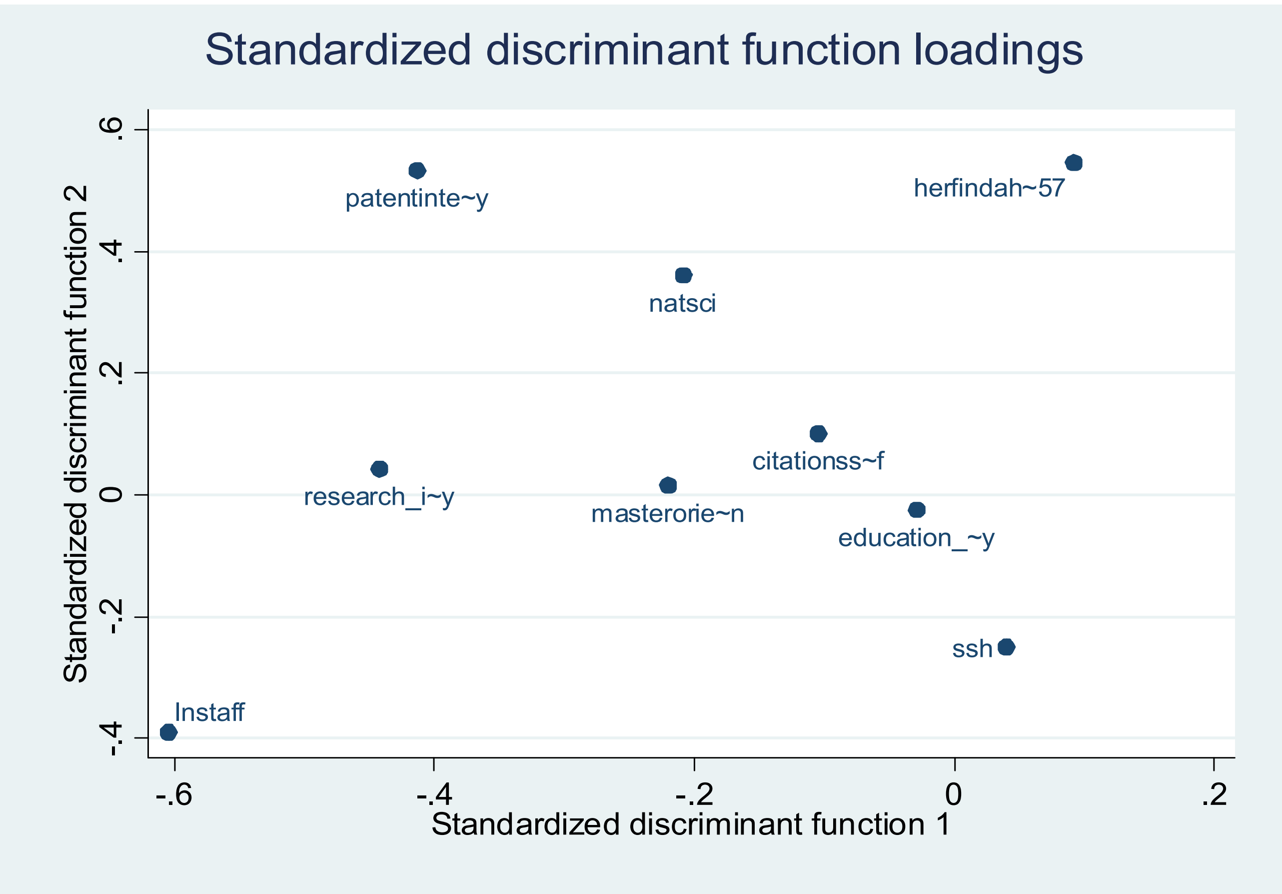
While the groups have their identifying features, this also analysis also display some cases where a more fine-grained classification would be useful, such as further dividing the research universities, respectively some cases which should be reclassified, such as the large generalist colleges that have been classified in class one rather than in class 5. This might be achieved either by refining the statistical model or by defining criteria for inclusion in the different classes.

4.2 An helicopter view of diversity

To put these classes in relationship, we use discriminant analysis, a statistical technique to identify which combinations of dimensions distinguishes different groups of cases (McLachlan, 2004). As shown by Table 6, discriminant analysis identifies two factors, which account for most of the differences between the classes. The loadings of the observed variables allow for a simple interpretation: factor1, which accounts for three-quarters of the variance, is strongly associated with research intensity, while factor 2 is associated with subject mix, distinguishing between HEIs oriented to natural sciences and those oriented to social sciences and humanities.

Table 6. Discriminant analysis (5-class model)

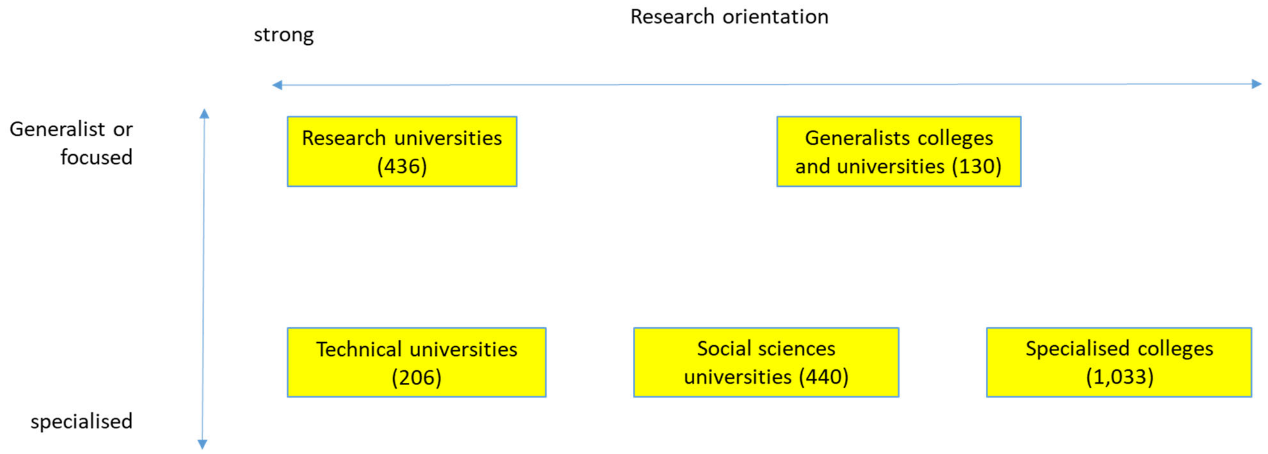
	Canon.	Eigen-	Variance		Likelihood				
Fcn	Corr.	value	Prop.	Cumul.	Ratio	F	df1	df2	Prob>F
1	0.8469	2.53677	0.7655	0.7655	0.1503	136.37	36	7459	0
2	0.6201	0.624716	0.1885	0.954	0.5315	58.583	24	5775	0
3	0.2894	0.09138	0.0276	0.9816	0.8636	21.647	14	3984	0
4	0.2397	0.06097	0.0184	1	0.9425	20.252	6	1993	0



Based on this analysis, classes can be described in terms of two dimensions in our framework as in Figure 4:

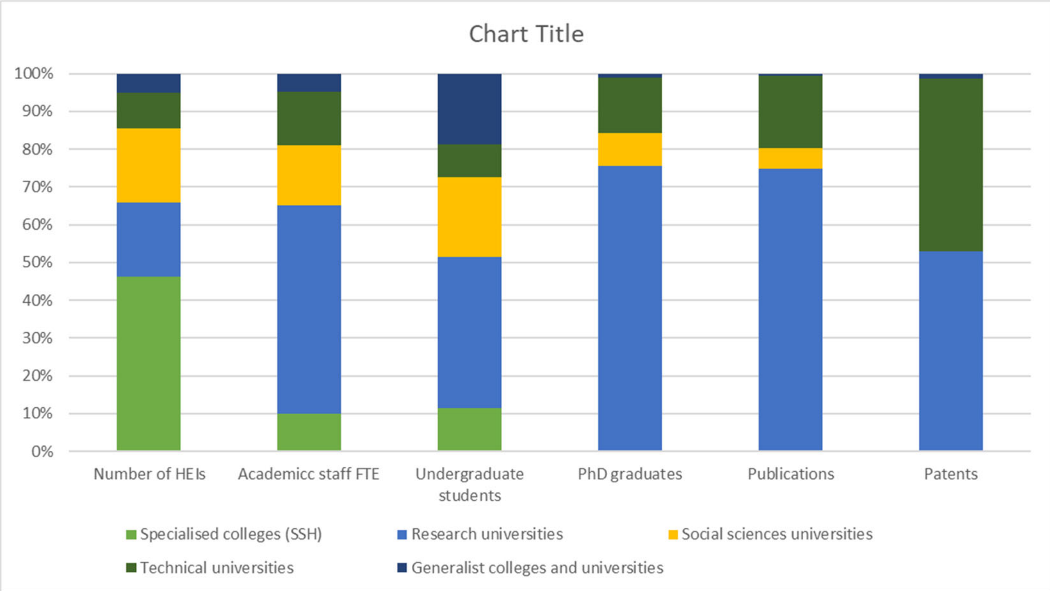
- The subject profile of HEIs. The model identifies two classes of HEIs covering most scientific fields, as shown by the low score for the subject specialization variable, and two specialized classes that focus on a specific subject (technology vs social sciences and humanities).
- The orientation towards research from the top-universities group to HEIs with no research activity.

Figure 4. Characterization of classes



Finally, Figure 5 display the importance of each class in terms of the share of activities they account in the whole system. The core of European higher education is clearly accounted by group 2, i.e. the research universities. However, in terms of undergraduate education, social sciences universities and generalist colleges account for an important share, while technical universities produce half of the patents in the whole system with only 10% of the student enrolments. Classes therefore correspond to distinct roles within the system.

Figure 5. Percentage of activities accounted by each class



5 Discussion

In this paper, we have developed a methodological and statistical approach to HEI heterogeneity that builds on conceptual modelling to introduce the relevant dimensions for classification, but then derives endogenously the HEI classification from the data. As such, the approach is more flexible than purely ex-ante classifications like the Carnegie classification in the US (McCormick and Zhao, 2005) and, unlike data-driven clustering, allows introducing prior assumptions on the impact of regulatory characteristics in the classification model (Schubert et al., 2014).

At the substantive level, the model represents the heterogeneity of European higher education along two main axes, i.e. the orientation towards research vs education and the extent of subject concentration; other characteristics, like education or technological intensity, by large follow these axes. While this might have been expected, the model provides more fine-grained distinctions.

Along the research orientation dimension, we singled out classes that are readily interpretable in terms of the HEIs belonging to them. Expectedly, universities tend to concentrate on the research side and colleges (non-PhD awarding) on the educational side, but there is a significant extent of blending, showing that comparing universities and colleges as homogenous groups falls short of accounting for the diversity of national and historical situations. Moreover, this analysis shows that, while there is significant overlap between research and education function, nevertheless distinct groups of research vs. education-oriented HEIs have emerged.

On the subject specialization side, the model moves beyond the distinction between generalist and specialists to identify those groups of specialists that a) are distinctive in terms of their characteristics and b) are numerous enough to show up in the classification.

Finally, we suggest two future extensions of this work. At the methodological level, we envisage refining the battery of indicators and, possibly, testing some more indicators for third-mission activities; the sensitivity of the results with respect to the selection of indicators, to the model specification and to the initial conditions needs to tested thoroughly to ensure the robustness of results. At the substantive level, we envisage developing the interpretation of the classes in terms of ideal-types and of their association with non-observable characteristics like HEI identity and/or institutional mission. This might be achieved by using additional variables for interpretation, such as the foundation year, but also through more in-depth analysis of individual cases.

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