Research Proposal

Developing a taxonomy for profiling innovative firms

1 Introduction

In research and policy-making concerning innovation it is often convenient to group firms with similar characteristics according to some kind of classification. More on use of groups: e.g. public funding, innovation policies,… Examples of policies that aim at a specific sector group, e.g. from the Barcelona objectives.

Many of these analyses have been based on comparing sectors (on NACE, NAICS, ISIC or ICB) or sector groups, such as the OECD's low-tech vs. high-tech classification (e.g. based on R&D intensity, see Hatzichronoglou, 1997) and Pavitt's taxonomy. Although these methods are widely used and general patterns of innovation behaviour can be distinguished, these classifications have some weaknesses. Sectors consist of heterogeneous firms that behave differently, especially concerning innovation. For example, the OECD classification (ranging from Low to High R&D Intensive consist of sectors that *on average* can be distinguished and grouped by their R&D intensities. However, it might be obvious that not all firms from the Pharmaceuticals & Biotechnology sector have high R&D intensities or that all firms from Industrial Metals have very low R&D intensities. Firms in the latter sector, for example, might be very innovative, either due to investing in R&D or by other means. Besides, some service sectors, now often left out of classifications have different innovation profiles (e.g. Banking and Travel & Leisure, see Evangelista, 2001). For Pavitt's taxonomy – besides the fact that sectors are clustered rather than firms – it is also the case that it only takes into account innovative firms and not non-innovative firms. This leads to a high degree of variance found within each sector group.

The aim of this research is to develop a tool for analyzing innovation behaviour without losing sight of specific firm characteristics and by looking at more indicators of innovation activities. This will be done by primarily classifying *firms* (and not sectors) and therefore taking into account sector and firm heterogeneity. Archibugi (2001) stated that a technology-based classification of firms loses much of its relevance if it is applied to firms after aggregating them into sectors (based on output), i.e. it should be independent from other criteria. By following the initial work of Cesaratto and Mangano (1993), this research aims at applying a cluster analysis by using Community Innovation Survey data and as such to classify firms by identifying some variables that describe better the innovation profile of the firms.

Cluster analysis is a tool for exploring the structure of data. The core of cluster analysis is the process of grouping objects into clusters such that objects from the same cluster are similar and objects from different clusters are dissimilar. Objects can be described in terms of measurements (e.g. attributes, features) or by relationships with other objects (e.g. pairwise distance, similarity). In this work, firms – without taking into account the *ex ante* sector, country, firm size and economic performance – will be clustered into groups on basis of the variables that describe the R&D profile of a firm.

2 Literature

This paragraph will provide a review on literature on innovation. This will help by finding the right set of variables for defining a firm's innovation strategy. First, the classifications as mentioned earlier will be explained in greater detail in order to learn more about crucial parts that determine a firm's innovation behaviour. Second, literature on innovation behaviour on firm level will be reviewed.

2.1 Taxonomy

Leastedius et al (2006)

The term "taxonomy" is generally used for the classification of empirical entities. Taxonomies facilitate communication due to a "common understanding". The creation of a taxonomy has the intention of bringing order into the science or discourse in question, which is done by reducing a large set of phenomena to a much smaller set of classes of phenomena which may facilitate analysis and open a path for new the way for discoveries.

The essential requirement of a taxonomy needed to make it useful is that it is convincing enough to obtain legitimacy within the relevant community, by economising communication and knowledge formation processes within a defined domain. As such, it creates a model that limits and directs further search and policy activities.

Legitimate taxonomies take into account the following criteria: simplicity, reliability, relevance, adaptability and community creation. For a discussion on this, see Leastedius et al (2006).

2.2 Low-tech vs. high-tech

The term "low-tech sectors" is widely used by researchers and policy-makers. Often is referred to a wide range of *mature* sectors (e.g. textiles, wood, mining, metals), without taking into account an official sector classification. The original low-tech vs. high-tech classification was aimed at the manufacturer industry and was made after ranking the industries according to their average R&D intensity (R&D/total output) over 1991-1999 (see Table 1). The classification concerns OECD countries, although for individual countries, allocation to the technology groups may differ.

The classification has as main advantage its usability: it consists of four clearly defined groups (simplicity) of which the only used variable (R&D intensity) is rather simple to measure and data are publicly available (reliablility).

However, nowadays, new and old technologies are used combined. This means that low-tech products might also consist of high-tech technologies and vice-versa (for example biotechnology in food producers). Therefore, this classification is becoming less and less useful for academic analyses (Von Tunzelmann and Acha, 2005). However, data gathering and policy-makers still make widely use of this classification.

Technology group	*R&D intensity*
High-tech industries	R&D intensity: > 5%
Medium high-tech industries	5% > R&D intensity > 3%
Medium low-tech industries	3% > R&D intensity > 0.9%
Low-tech industries	0.9% > R&D intensity > 0%

Table 1 OECD Classification of innovativeness based on R&D intensity

Sectors that fall into the group of low-tech sectors are Textiles (textile products, leather & footwear), Wood (products of wood & cork), Pulp (paper, paper products) and Manufacturing (recycling and n.e.c.). These industries have fairly standardised production processes and product design. In this context set-up costs are low and a large number of firms compete fiercely on price (Scarpetta and Tressel 2004).

For using the classification as of classifying firms on basis of innovativeness, it has some serious shortcomings. It is often wrongly used to identify innovative sectors by assuming that that all firms from high-tech sectors are by definition innovative and all firms from low-tech sectors are by definition not. As such, innovation potential from firms beforehand labelled as non-innovative is neglected, while other firms that do have access to innovation funding and support, but not make use of this, since these firms do not innovate by definition.

Many activities can be classified as creative and innovative but which normally are not identified like that. Examples are design (for example in architecture, but also in textiles), software creation, and consultancy. To the extent that products are new, one can argue that they should be considered as innovations. The Oslo Manual states that, although such innovations have no clear “technological height”, are innovative and often difficult to handle and therefore excluded from consideration by both politicians and researchers.

2.3 Pavitt's taxonomy

Pavitt (1984) defined another sector taxonomy that takes into account the sources of technological change, requirements of users, and possibilities for appropriation. In contrast with the OECD classification that considers the product characteristics, Pavitt's taxonomy looks at processes and inter-industry links. Firms are classified into four groups: 1) supplier dominated, 2) scale intensive, 3) specialised suppliers and 4) science based. Sectors that we consider as low-tech (or low R&D intensive) can be found mostly in the first group. This supplier dominated group is characterised by firms that are generally small with weak in-house R&D and engineering capabilities. Professional skills, aesthetic design, trademarks and advertising play a more important role for innovation and technological trajectories are therefore defined in terms of cutting costs. Supplier dominated firms make only a minor contribution to their process or product technology. Most innovations come from suppliers of equipment and materials, although in some cases large customers and government-financed research and extension services also make a contribution

2.4 Other taxonomies and classifications

2.5 Going to the firm level

See Archiburgi (2000) and Cesarratto & Mangano (1992)

3 The dataset

3.1 Community Innovation Survey

The data for this research come from the anonymised[1] CIS3/4 database for 15 European countries. This survey collects data on firms' innovative activities, outcomes, barriers, but also

[1] At European Commission DG JRC IPTS, we have the possession of CDROMS with CIS3 and CIS4 (from January 2009 onwards) anonymised data. The work with anonymised data is merely an experiment for what can be done by using real firm-level data. The intention is to use real firm data when the research is in a more advanced stage. These data can be accessed at the so-called Safe Room of Eurostat in Luxembourg. I will have access here at the end of March 2009.

on funding and general firm characteristics. For characterizing a firm's innovation strategy, a selection of variables has to be made (see Section 4.1).

Disadvantages: only cross section data (only limited number of variables are collected over 2 year period)
Advantages: very detailed data on innovation activities (internal and external R&D, acquisition of R&D, machinery, other knowledge), many observations, many countries (with regional details available in Luxembourg.

3.2 Population characteristics

Present statistics on e.g.:
- firm size, age
- number of innovators
- sector representation
- innovation activities
- innovation output

Table 2: Descriptives of innovative firms

	N	*Min*	*Max*	*Mean*	*Std. Dev.*
Basic firm characteristics					
Turn (in million euro)	3219	0	13900.0	73.1	518.3
Exp (in million euro)	3211	0	3670.0	16.8	152.5
Innovation activities					
coop_research	3217	0	1	0,16	0,366
coop_market	3217	0	1	0,16	0,369
otherinnact	3217	0	1	0,79	0,408
exp_by_turn	3199	0	1	0,18	0,254
rrdinx_by_turn	3199	0	5	0,03	0,137
rrdexx_by_turn	3180	0	7	0,01	0,167
rmacx_by_turn	3198	0	21	0,04	0,508
roekx_by_turn	3179	0	9	0,01	0,178
rd_by_turn	3199	0	5	0,03	0,137
rothx_by_turn	3196	0	0	0,00	0,000
ta_by_turn	3172	0	21	0,05	0,543
rtot_by_turn	3206	0	30	0,10	0,769
Innovation performance					
inpdt	3219	0	1	0,72	0,451
inpcs	3219	0	1	0,71	0,455
turnin	2990	0	1	0,23	0,287
Valid N (listwise)	2913				

4 Methodology

4.1 Variable selection

For selecting the variables that define a firm's innovation profile, we will make use of indicators as used by the PILOT-project.

The PILOT-project formulates 6 indicators that grasp the innovation profile of firms (cf. Laestadius et al. 2006 for more details), namely

- R&D intensity
- Design intensity
- Technological intensity
- Skill intensity (human capital orientation)
- Innovation intensity
- Organizational innovativeness

Bender: The basic assumption is that these indicators together will capture the bulk of creativity, explaining successful firms and industries and showing the variety in all economic sectors. Thus we argue that the adoption of a family of indicators rather than a composite indicator is a more appropriate way to improve on available taxonomies.

For clustering firms, Cesaratto and Mangano (1993) used three groups of variables characterizing a firm's technological profile:

1. Technological input:
2. Technological output
3. Impact of innovations on sales

For making the clustering process feasible and meaningful, it is good to maintain the input-output-result line of the work of Cesaratto and Mangano (1993), while combining it with the innovation profile of the PILOT project. As such, the innovation profile is captured, while also the successfulness of a firm's efforts is taken into account. Therefore, the following set of variables has been selected for the clustering of the firms, divided into three groups:

1. Technological innovation input: the main strength of the CIS database is the detailed information about innovation inputs. Expenditures on internal and external R&D are provided, and also expenditures on acquisition of machinery, other knowledge and other inputs (such as training, marketing and design). Besides these innovation inputs, there is more information about whether a firm is involved in cooperation for its innovation activities, although this is a dummy variable.
2. Non-technological innovation input: organizational innovation, innovation collaboration, skills.
3. Innovation output: share of sales, process innovator

This is a total of x variables. The selection of these variables implies that no distinction will be made *ex ante* on country, region or sector. This will lead to clusters of firms with similar innovation profiles active in different sectors and countries.

4.1.1 Option 1:

rrdinx_by_turn
rrdexx_by_turn
coop_research

rmacx_by_turn
roekx_by_turn
rothx_by_turn
otherinnact

coop_market

inpdt
inpcs
turnin

4.1.2 Option 2:
R&D

Technological acquisition
ta_by_turn

Other innovation activities
Coop

Innovation outcome:
inpdt
inpcs

4.1.3 Option 3:

4.2 Cluster analysis

4.2.1 Obtaining new variables
Due to the large amount of variables, a *principal components analysis* will be applied in order to define new variables that synthesize the information by the original variables. This method permits the determination of new variables (components or factors) whose linear variability represents the variability of the original data matrix and its information contents with a sufficient degree of approximation (a similar procedure has been used by e.g. Miller & Blais, 1991; Fabbris, 1983). The justification for this step: 1)

4.2.2 Detecting outliers
Note: methods and results below are applied and obtained by clustering data from the EU R&D Scoreboard and by applying different cluster variables (input: R&D and capital intensity; output: sales; performance: profits). It is to illustrate what can be obtained.

Outliers represent non-representative objects for the general population or an undersampling of actual groups in the population that causes an underrepresentation of the groups in the sample and make the derived clusters unrepresentative of the true population structure. In this research, the following rules of thumb for detecting outliers were adopted:

- One of the clustering variables shows a missing value;
- Firms that reported higher profits than sales in the same year (due to factors – such as spinning off of one part – that have an extreme impact on profitability)
- Firms that invested more in R&D than the net sales of the same year AND reported losses higher than the net sales in the same year;

- Firms that had higher capital expenditures in than the net sales in the same year AND reported losses higher than the net sales in the same year.
- Firms with very low R&D intensities (<0.5%) AND very low capital expenditures (<0.5% as percentage of the net sales);

For the EU this meant that 120 of 1000 companies were deleted. These rules were chosen since these firms because of their "extreme" behaviour. Some (interesting) firms have extreme values for R&D intensity and profitability. In principle, this should be seen as 1 (or very few) cluster(s), because of the nature of these firms. However, the dissimilarity among these firms is so big that they represent each a different cluster, while less extreme cases are then grouped all in one enormous cluster (90% of all observations).

4.2.3 Standardizing the data

The selected variables are at ratio-scale. This might lead to difficulties when due to the characteristics of the data.

Milligan and Cooper (1988) showed that standardization methods involving division by the range offer the best recovery of the underlying cluster structure. Therefore, I applied the method as mentioned by e.g. Anderberg (1973):

$$Z = \frac{X}{\max(X) - \min(X)} \qquad (1)$$

4.2.4 Principal component analysis

SPSS two-step procedure

4.2.5 (Dis-)similarity measures

Inter-object similarity is a measure of resemblance between objects to be clustered, and therefore fundamental to cluster analysis (Hair et al., 1998). For this research, I will make use of Euclidean distance measure in order to measure the inter-object similarity. It represents the similarity as the proximity of observations to one another across the variables in the cluster variate. The distance measure is actually a dissimilarity measure, because it represents the distance between two objects. A larger value represents a lesser similarity.

4.2.6 Selecting a cluster algorithm and determining the number of clusters

When the variables are selected and the similarity matrix is calculated, the algorithm for the cluster formation must be selected. The question is which set of rules is the most appropriate to place similar firms in a cluster? In this paragraph, the foundation for the used algorithm will be explained.

Hierarchical cluster algorithms:

- Agglomerative algorithms start with each observation being considered as a separate cluster and then clustered on basis of (dis)similarity measures
- Divisive clustering algorithms start with one cluster containing all observations and splitting up to several groups on basis of (dis)similarity measures

Partition clustering algorithms:

- Break the observations into a distinct number of non overlapping groups

- Beforehand the number of clusters must be defined
- Two methods:
    - o K-means: each observation is assigned to the group whose mean is closest
    - o K-medians: as with kmeans, but with medians in stead of means.

The partition clustering algorithms are more suitable for larger datasets, but must be performed various times in order to find the optimal number of clusters.

For this research, I first applied various hierarchical cluster methods in order to see which number of cluster should be optimal for this dataset. Although the results of the stopping rules Caliński-Harabsz and Duda-Hart) varied a lot, it seemed that 5 groups can be seen as a minimum while 13 groups is a maximum. Subsequently, I applied the *kmedians* clustering algorithms on the dataset forming 5 to 13 groups with the Caliński-Harabsz stopping rule for comparing the clustering outcomes. The optimal outcome during this exercise is the use of 5 clusters.

The next paragraph will deal with the outcomes of the clustering process.

5 Results

The results of the clustering process for the top 1000 EU firms is presented in Table 3. The five clusters are explained in the following paragraphs.

Table 3 EU clusters

	Cluster 1	*Cluster 2*	*Cluster 3*	*Cluster 4*	*Cluster 5*	*Total*
# firms	189	195	120	341	35	880
% of firms	21.5%	22.2%	13.6%	38.8%	4.0%	100%
% of employees	14.4%	37.1%	4.5%	43.9%	0.1%	100%
Average firm size	14251	35810	7003	24078	498	21284
size distribution:						
SME (<250)	3.2%	1.5%	20.0%	0.9%	57.1%	6.4%
large (251-2000)	47.1%	18.5%	53.3%	17.6%	37.1%	29.8%
huge (>2000)	49.7%	80.0%	26.7%	81.5%	5.7%	63.9%
sales (million € per firm)	3066.2	12794.7	1709.3	5241.2	66.3	5760.4
sales ((thousand € per employee)	215	359	244	218	133	271
profits (% of sales)	8.2%	14.4%	18.5%	8.2%	-87.7%	11.6%
R&D (% of sales)	6.5%	1.2%	15.3%	1.1%	42.2%	2.4%
capex (% of sales)	4.1%	10.5%	5.1%	3.4%	6.6%	7.1%
R&D employees per firm	2579	2032	1905	794	340	1725
…(% of employees)	11.8%	4.2%	20.3%	2.2%	55.8%	6.7%
Marketcap (million € per firm)	4219.8	19233.0	4957.9	5553.6	600.0	8050.7

5.1 Cluster 1: "Large research intensive firms"- huge science based

- 21.5% of all firms, but only comprises 14.5% of all employees
- Average number of employees if 14251 (average 21284)
- 96.8% of the firms is large or enormous, only 3.2% is SME
- high R&D intensity (6.5% compared with 2.4% on average)
- below average capex intensity (4.1% compared with 7.1% on average)
- below average sales per employee
- below average profitability (8.2% compared with 11.6% on average)
- half marketcap per firm
- High percentage of R&D employees (11.8% compared with 6.7% on average)

Firms from sectors: mainly from "high-tech" sectors.

5.2 Cluster 2: "Production intensive firms"- scale intensive firms

- Comprises 22.2% of all firms and 37.1% of employees
- Highest average firms size of all clusters (almost 36000 employees)
- Logically: dominated by "huge" firms
- Low R&D intensive (1.2% compared with average of 2.4%)
- high capex intensity (10.5% compared with an average of 7.1%)
- highest sales per employee
- high profitability
- large (employees), around twice the average firm size
- high market capitalization, around twice the average firm size
- below average part of employees is R&D employee.

Firms from sectors: Many sectors involved, Electricity, Fixed Line Telecommunications, Automobiles & parts and Chemicals the largest.

5.3 Cluster 3: "Innovative Winners" – science based firms / specialized suppliers?

- Comprises 13.6% of all firms and 4.5% of employees
- One third of average number of employees (7000)
- High R&D intensity (15.3%)
- Just below average capex intensity (5.1%)
- Just below average sales per employee
- High profitability (18.5%)
- High share of R&D employees (20.3%)

5.4 Cluster 4: "Incumbent firms" – ?

- Largest cluster in terms of R&D number of firms (38.8%) and employees (43.9%)
- Just above average number of employees (24078)
- Cluster with the lowest R&D intensity (1.1%)
- Cluster with the lowest capex intensity (3.6%)
- Below average profitability (8.2%)
- Below average sales per employee
- Below average marketcap
- Small share of R&D employees (2.2%)

Firms from sectors: firms from "low-tech" sectors are overrepresented.

5.5 Cluster 5: "Gamblers"- science based

- Comprises only 4.0% of all firms and only 0.1% of all employees
- Smallest average firms size (498 employees)
- More than half of the firms is SME
- Largest percentage of R&D employees (55.8%)
- Very high R&D intensity (on average almost half of the total sales is invested in R&D)
- average capex intensity
- average sales per employee half of total average

- the only cluster where firms on average make (high) losses (87.7% of sales)
- smallest marketcap

Firms from sectors: More than half of the firms from Pharmaceuticals & biotechnology sectors. Other firms are from sectors that are considered as "high-tech", according to OECD classification.

6 Conclusions

Stepping away from the current sector groups low-tech – high-tech, as still used in many policy documents and research, might lead to a better grouping of firms based on their strategy, in stead of grouping firms on basis of one variable. In this research I followed the work of Pavitt (1984) and especially Cesaratto and Mangano (1993) by looking at firm strategies. Using data from the 2007 EU R&D Scoreboard, I defined the innovation strategies of firms on basis of three variables, namely R&D intensity and capital expenditures intensity (both as inputs to innovation) and profitability (as an output). Intentionally, sector and country were not taken into accounting in the clustering process. This implies that different innovation strategies can be found within the same sector and that comparable innovation strategies can be found among different sectors. This is neglected by the traditional low-tech vs. high-tech classification or ICB classification.

When applying cluster algorithms to the three selected variables, it turns out that five clusters of firms with alike strategies care formed. These five groups are recognizable and easy to identify. In some cases they are much overlapping with Pavitt's taxonomy.

The results are very dependent on the choice of the variables. Due to the availability of variables in the 2007 EU R&D Scoreboard, no information can be retrieved on innovation output (e.g. sales due to new products or introduced process innovations). Furthermore, capital expenditures is not an ideal measure for acquired technology (it also involves many other capital acquisitions). Labour productivity would be a better measure for firm performance, since it is not so much influenced by accounting standard as profitability is. However, the results are very satisfying and can serve as a good start to

7 References

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		inpdt	turnin	inpcs	rrdin	rrdex	rmac	roek	rtr	rmar	rpre	turn	coop_r	coop_m	p_form	P_trat	otherinn	Exp/turn	Rd/turn	Ta/turn
Outlier	N	42	36	42	42	42	42	42	41	42	41	42	42	42	42	42	42	42	42	42
	Mean	,83	,41	,69	,86	,26	,45	,31	,51	,29	,07	1,04E7	,60	,64	,26	,36	,74	,07	,84	1,83
	Std. Dev	,377	,359	,468	,354	,445	,504	,468	,506	,457	,264	3,19E7	,497	,485	,445	,485	,445	,151	,770	4,369
1	N	660	638	660	660	660	660	660	654	652	657	660	660	660	660	660	660	659	660	660
	Mean	1,00	,32	,00	,55	,19	,45	,17	,33	,31	,20	3,88E7	,16	,15	,34	,36	1,00	,18	,02	,02
	Std. Dev	,000	,293	,000	,497	,396	,498	,378	,471	,461	,403	2,01E8	,369	,357	,473	,480	,000	,242	,060	,084
2	N	194	185	194	194	194	194	194	192	192	192	194	194	194	194	194	194	193	194	194
	Mean	1,00	,32	,00	,44	,09	,37	,08	,14	,17	,14	3,65E7	,07	,09	,19	,21	,00	,14	,02	,02
	Std. Dev	,000	,327	,000	,497	,283	,483	,268	,349	,374	,343	1,77E8	,259	,283	,390	,406	,000	,230	,054	,074
3	N	1191	1093	1191	1191	1191	1191	1191	1179	1176	1168	1191	1191	1191	1191	1191	1191	1190	1191	1191
	Mean	1,00	,31	1,00	,70	,29	,65	,28	,51	,40	,27	8,77E7	,21	,22	,38	,45	1,00	,22	,02	,02
	Std. Dev	,000	,279	,000	,460	,454	,477	,448	,500	,489	,443	5,13E8	,409	,412	,485	,498	,000	,267	,052	,069
4	N	184	154	184	184	184	184	184	183	182	178	184	184	184	184	184	184	184	184	184
	Mean	1,00	,32	1,00	,47	,21	,58	,15	,32	,19	,14	1,19E8	,18	,18	,19	,23	,00	,20	,01	,04
	Std. Dev	,000	,328	,000	,501	,406	,495	,355	,467	,391	,348	1,03E9	,389	,385	,394	,421	,000	,265	,060	,082
5	N	578	578	578	578	578	578	578	577	567	568	578	577	577	578	578	578	577	578	578
	Mean	,00	,00	1,00	,28	,16	,73	,21	,33	,10	,14	6,55E7	,07	,09	,16	,21	1,00	,14	,01	,03
	Std. Dev	,000	,000	,000	,447	,365	,443	,405	,470	,303	,350	6,07E8	,257	,282	,365	,407	,000	,238	,024	,064
6	N	59		59	59	59	59	59	58	57	59	59	59	59	59	59	59	59	59	59
	Mean	,00		,00	,53	,24	,25	,05	,19	,05	,14	2,81E7	,20	,15	,07	,12	,58	,16	,01	,03

	Std. Dev	,000		,000	,504	,429	,439	,222	,395	,225	,345	5,49E7	,406	,363	,254	,326	,498	,253	,013	,145
7	N	257	257	257	257	257	257	257	256	255	257	257	257	257	257	257	257	257	257	257
	Mean	,00	,00	1,00	,21	,10	,61	,12	,19	,04	,08	2,08E7	,06	,07	,07	,11	,00	,13	,01	,04
	Std. Dev	,000	,000	,000	,411	,302	,488	,326	,391	,185	,268	5,79E7	,242	,256	,256	,307	,000	,234	,043	,089
Total	N	3165	2941	3165	3165	3165	3165	3165	3140	3123	3120	3165	3164	3164	3165	3165	3165	3161	3165	3165
	Mean	,72	,22	,71	,52	,21	,59	,21	,37	,26	,20	6,46E7	,16	,16	,27	,33	,79	,18	,03	,05
	Std. Dev	,451	,285	,455	,500	,409	,492	,405	,483	,439	,397	4,89E8	,365	,368	,446	,468	,409	,252	,138	,544