TOBAM*
CORE INVESTMENTS

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# DIVERSIFICATION DASHBOARD

## Research Insights from Outside the Box

# Company Sector Classifications
## Original research, actionable insight

### A note from the Research desk…

Did you ever wonder about why actually we talk so much about sectors when it comes to investing and financial markets' behavior? In fact, classifying companies according to their respective main sector of activity is a common practice in finance of trying to use a company's sector as a proxy for its potential main risk exposure.

In this note, we dig deeper into how this definition is actually made and could be improved in an out-of-the-box way. As we argue in our note, the problem of currently widely used sector classification methods such as Global Industry Classification Standard (GICS) as applied by MSCI, S&P and other index providers suffers from the fact that the discretionary and fundamental ways of classifying sectors might underscore the true risk drivers to which a company is exposed. Fundamentally speaking, what sector best represents the main risk driver for Tesla: Automobile manufacturing or Information technology? And what about Amazon? Clearly this company's business model has changed a lot since it was first assigned to a certain sector. And after all, beyond fundamentals, what is really relevant to assess risk is also the market's perception, which is best reflected in asset prices.

In this study, our perspectives are based on what we have acquired a lot of knowledge about over the last decade(s), i.e., risk exposures or correlation and we use them in the context of machine learning algorithms that can help to improve the heuristic methods used in sector classifications so far. The final aim of this exercise is to come closer to the objective of reflecting in the best possible way the appropriate sector related risk exposures of a company in a timely manner.

The results clearly highlight that there is a lot of room for improvement for traditional sector classifications schemes and that encouraging the complementary use of quantitatively driven and qualitative classification schemes would be probably very valuable for investors who want to understand better the risks within their portfolios and respond in a timelier manner to changes in activities of companies and hence the risks to which they are exposed.

We hope this note provides you with as many useful insights as it has done for us.

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# Company Sector Classifications

### *Introducing clustering models*

In this note, we study models that assign stocks to statistical clusters, based on their returns, and indirectly, using similarities defined as functions of the correlation matrix. To compare what we propose with commonly used methods of sector classification, we employ the very widely used GICS classifications as the point of reference for our proposed solution.

We present criteria used to select the best amongst many clustering models, where a key ingredient to this procedure is the closeness to the GICS sector classification. Indeed, it is important to stress that no model is perfect. As such, it is reasonable to incorporate GICS sector information that are made by humans and based on economic grounds to validate statistical cluster models. We then compare these clusters to actual GICS sectors of the MSCI USA, EMU and Japan.

### *Comparison vs MSCI sectors*

Our results for the MSCI USA, EMU and Japan for a sample period from 01/2016-01/2018 highlight that the methodology of sector classification that we propose allows us to discover new clusters of sectors and hence allows for a more appropriate and complete identification and representation of risk exposures than those of GICS classifications. It also helps to justify the changes made in 2016 to the GICS sector classifications, when Real Estate was added as the 11th sector. In fact, one would have even been able to predict this change, which means that our model is able to react in a timelier manner to fundamental changes in the sectoral structure of an investment universe that go potentially along with changes in the structure of risk drivers, which makes it desirable to detect as early as possible such changes. Moreover, we also find that the reclassification of certain IT stocks into the Communication Sector in 2018, purely from a risk exposure or correlation point of view was not a good decision. Finally, we also observe, using our new methodology, that adding at least one more additional sector group would be more than justifiable given the apparently large differences in risk exposures between the banking- and insurance-related companies in the financial sector.

In the analysis we first explain the GICS methodology. Thereafter, we define the criteria that we intend to use to evaluate the quality of our model. Next, we review several models and we apply them to the sector classification problem and finally chose one model based on the pre-defined criteria. Finally, we analyze the resulting clusters/proposals for sector classifications and compare them with GICS. In this note we mainly focus on results for the US market with a few comments regarding EMU and Japan. We are happy to share more detailed results on these two regions upon request.

## I. Classification in the "GICS way"

### *A revenue-based sector classification*

The GICS methodology starts classifying stocks by assigning them to a given industry. To this end, it relies on companies' annual reports and accounts, published research and broker reports. The general rule is to look for the industry that corresponds to the commercial activity that generates more than 60% of the total revenues of the company. If the company has more than one activity and none of them generates more than 60% of the company's revenues, the company is assigned to the industry that corresponds to the commercial activity with the highest revenues and earnings. If no valid industry can be identified in this way, the company's activities are investigated further, and the sub-industry that seems to be the most adequate is defined in a discretionary way. However, in the case where the company has diverse activities that belong to different sectors and none of these contribute in a predominant way to the revenues or earnings, it is as a consequence classified either in the Industrial Conglomerates industry (Industrial Sector) or in the Multi-Sector Holdings industry (Financials Sector). The other levels are then identified in a bottom-up approach. The classification is updated either on a yearly basis or upon a company's request or a corporate restructuration.

### *Sector classification biases*

Determining sector classifications in this way is potentially prone to biases and classifications that incorporate only relatively late once the business model and hence also the risk structure of a company changes. For instance, if we look at Tesla, it is considered as an automaker, and hence is part of the consumer discretionary GICS Sector. Tesla is increasingly perceived by the market as a technology company due to its technological innovations and cutting-edge engineering where technology is core to its automaking infrastructure. Looking through the lens of correlations, Tesla exhibits a Pearson correlation of 40% with the IT sector as compared to 35% with the Consumer Discretionary sector. Another example is Netflix, considered by GICS as a media company, that provides content to its customers, and is as a consequence part of the Communication Services Sector, while it can also be considered an IT company since it is a tech-powered streaming company that relies on internet to provide its services and content. Netflix has a correlation of 41.2% with IT and 41.3% with Communication Services. A final example would be Annaly Capital Management, considered as one of the largest mortgage real estate investment trusts in the US, is considered by GICS as being part of the Financials sector while it should be more of a Real Estate company. Annaly Capital's correlation with Real Estate is 46% while it is correlated only at a level of 10% with Financials.

To address these potential issues and to improve to what extent sector classifications capture actual risk exposures, it could hence be interesting to investigate an approach that is free of discretionary choices and that relies on what reflects best actual risk exposures, i.e., the correlation structure of an asset.

## II. Correlation-Based Sector Classification

If we want to find the best way possible to classify N stocks into K distinct groups, based on their actual difference in risk exposure, which could for instance be measured by using their pairwise correlations, the feasibility of looking at all the different partitions becomes impossible as K or N grows. To overcome this issue, we need to use alternative ways that are computationally feasible.

### *Defining the ideal classification model*

Our approach uses unsupervised-learning methods to partition the universe of stocks into K disjoint clusters. Such methods try to find a subset of all the possible partitions that might contain a good sub-optimal partition and hopefully the optimal one. The idea is to find a model or an ensemble of models that are good enough candidates to complement the GICS classification and allow us to derive meaningful conclusions, while being able to fill-in the missing sectors.
But what is the definition of good enough? How can we compare different classification methods to find the best one while being close but different from GICS? To answer these questions, we need to define metrics and indicators that will help to fulfill the tasks at hand.

We start by providing a high-level definition of an ideal model[1]:

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Definition

A model for sector classification is "good enough" if it satisfies the below criteria:

1- It is stable across time → Stability.
2- It is close to a reference model → Similarity.
3- Most of the companies of a given cluster belong to the same reference sector → Homogeneity.
4- Stocks in the same reference sector are assigned to the same cluster → Completeness

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[1] Note, we take the freedom of defining ourselves the standard of a "good" sector classification model, without specifically citing here a source that would provide backing for our definition given that we have ourselves an extensive long-standing experience and own standards when it comes to model quality. Moreover, each problem demands a somewhat tailor-made definition of quality criteria to best meet the model's purpose. Obviously, these standards are also in large parts derived from various sources and proposals made by other experts in the field.

The critical part is to define a "natural" order between the metrics. Indeed, we already saw that we cannot use homogeneity as the most important criterion. The same applies to completeness: because a cluster containing all the stocks is complete (all the stocks of the same sector do belong to the same cluster), the resulting cluster is useless and far from being close to any economically meaningful way of sector clustering. We are left with the similarity criterion, but this latter is not ideal either, in the case when the number of clusters exceeds the number of sectors for example. The metric decreases with an increasing number of clusters: A perfect similarity between the model and a reference model is a 1-to1 mapping between the sectors and the clusters. We are left with a reasonable solution that does neither depend on the number of clusters, nor the number of sectors. It is the result of a tradeoff between homogeneity and completeness. In what follows, we account for this tradeoff by taking the harmonic mean between the two metrics, which we call the V-measure. If we denote h the homogeneity measure and c the completeness measure, then the V-measure is defined as:

$$v = \frac{2hc}{h + c}$$

Consequently, we propose the following hierarchy of model evaluation criteria:

| 01 | 02 | 03 | 04 |
|---|---|---|---|
| Time stability | V-Measure | Homegeneity | Similarity |

To put this into perspective, a 1% difference in annualized returns over a period of 30 years is roughly equivalent to a difference of 33% of the terminal value of the investments.

## III. Sector Classification Using Unsupervised Learning Methods

In what follows, we first briefly describe the different classification algorithms that we used. Thereafter, we use the US market as an example to show how these different models perform and what method we retained. For the sake of brevity, the results of many results and robustness checks are not included but are available upon request.

### *Clustering models*

K-means clustering algorithm

The K-means algorithm partitions the data points in a sample (let's say stocks here) into K partitions in an iterative way. It starts by selecting randomly K points from the sample data that act as centroids. Then it performs an iterative process that tries to find the nearest cluster and then defines a new centroid as the center of the points belonging to the cluster until either the maximum of iterations is exceeded, or the cluster assignments stop changing.
The advantages of using the K-Means algorithm resides in its simplicity and the fact that we are guaranteed a convergence at least to local minima[2]. However, the algorithm performs badly when the clusters have different sizes and shapes, or in the case where the data points are not linearly separable. Moreover, there will be clustering uncertainty of certain points, which cannot be evaluated by the method.

Gaussian mixtures algorithm

The Gaussian Mixture algorithm is a parametric model that uses the EM-algorithm to assign the data points to a given cluster. It assumes that the data is generated from a mixture distribution. This model has the characteristic of providing a flexible way of representing the points into clusters without restricting each data point to a single cluster, it has the advantage of being a probabilistic model and hence adds more information about the structure of the data as measured by their covariances and means. It also provides us with the possibility to identify potential points (stocks here) that are further away from all the distributions and hence are potential outliers. However, the Gaussian Mixture model suffers from the same drawbacks of the K-Means algorithm, namely identifying the optimal number

[2] The algorithm can be viewed as a coordinate descent algorithm where we minimize for $k$ in the first step then for $c_k$ in the second step.

of clusters, converging to local optima, high sensitivity to the initialization step and the need for large datasets to better estimate the parameters of the model. The algorithm might also diverge strongly if we have few data points.

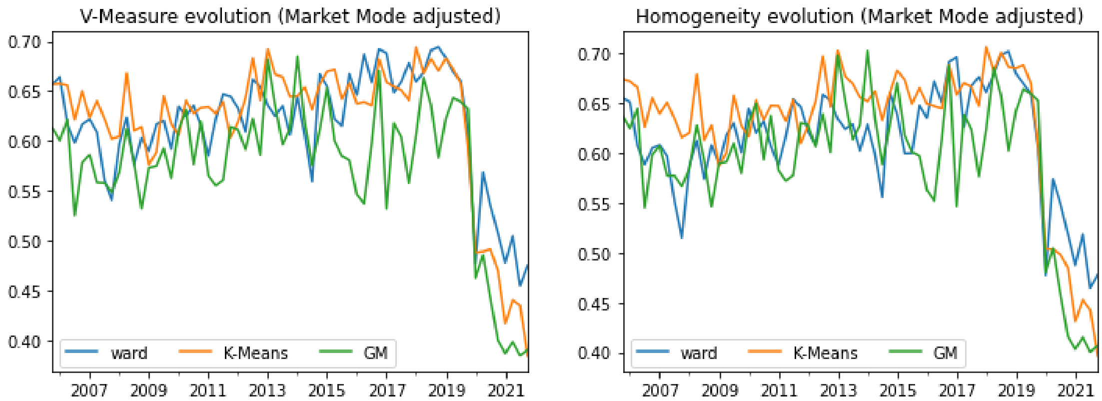
Hierarchical clustering algorithms

The agglomerative hierarchical clustering technique uses tree-based cluster construction in a bottom-up fashion. It starts by assigning each point to its own cluster, then, at each iteration, two clusters that have a minimal distance are merged until there is a single cluster that contains all the data points. A Dendrogram allows the representation of such structure, where the height of two merged clusters represents the distance or degree of difference between them. Different linkage methods are used to determine the distance between the clusters, we will focus here on the Ward method. The hierarchical clustering is the most intuitive model among all of the models applied here, due to its simplicity and how the clusters are formed based on the criteria mentioned above. Moreover, the data is structured, which provides extra-information. However, it is not always possible to identify the appropriate number of clusters by using the dendrogram and in this case one should rely on other methods.

## *Choosing a clustering model*

To evaluate the stability of the metrics of our models, the period between Jan 2006 until June 2021 is considered. We report in what follows the results for the MSCI USA. We run our models on a 3-month rolling basis and at each time-period we use a correlation matrix computed on 3 years of daily asset returns. The metrics are then computed based on the predicted clusters of the period, namely: Homogeneity, completeness, V-Measure and similarity (measured with the adjusted Rand Index). Figure 1 below highlights that the hierarchical clusters computed using the Ward algorithm competes with K-Means and Gaussian Mixtures for the USA Universe. However, in the results for EMU and Japan we find that the Hierarchical clustering works best. Moreover, we verified the variability of the different metrics over time for a 3-month rolling clustering and found again that the Hierarchical Clustering using the Ward linkage performs very well. Hence, we will focus in what follows on this method.

Figure 1: Evolution of the evaluation criteria for the different classification methods over time for the MSCI USA investment universe (Jan 2006 – Jun 2021)




*Source: Bloomberg, TOBAM.*

## *Empirical Results*

We next proceed to the mapping between the clusters and their corresponding sectors by assigning the sector that is the most likely to be observed, i.e., we choose the sector with the highest observed to expected ratio.

Before detailing the results, for the fast reader, and for the sake of brevity we do not show here the results for all universes, we can summarize the following key takeaways:

1) MSCI USA: based on our model, the **Real Estate and the Insurance industries are separated from the Financials sector**. While the Real Estate sector has been promoted to become a sector of its own in 2016, we might argue that the insurance industry is a good candidate to become the 12th sector. Moreover, we might

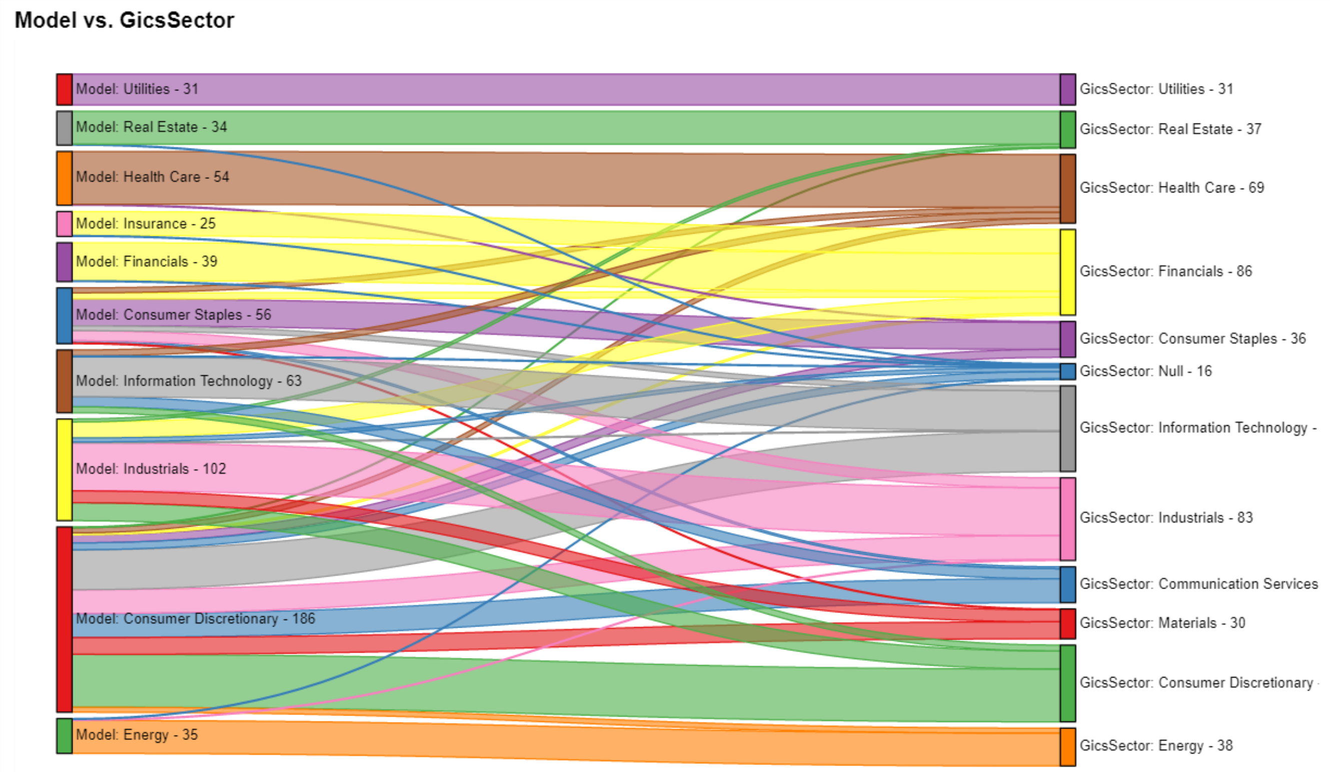
expect some restructuring of the GICS classification at various sector levels. For instance, the Materials sector seems to have a significant share of heavy industry companies, that should better be classified in this way, while others are more Consumer type of stocks. One should bear in mind that within these assignments, there are potential outliers, and some clusters are too complex to be clustered appropriately.

2) MSCI Japan: in this region we observe that while a split of the Financials and Insurance sectors seems to be less of an obvious need, there are other sectors such as Consumer Staples, Consumer Discretionary, Communication Services and IT that seem to contain a lot of companies that as classified with a heuristic approach do not find their true risk exposures well represented by the assigned sectors and a correlation-based approach can provide here important additional insights.

3) MSCI EMU: given that the EMU has a very large and competitive automotive manufacturing industry, one very obvious need for change of traditional GICS classifications is that throwing these into the same category the other Consumer Discretionary stocks would misrepresent the true risk exposure they represent. Moreover, the rest of the official GICS Consumer Discretionary stocks exhibit risk exposures that actually make them look extremely similar to IT companies, which implies that in EMU there probably is no real Consumer Discretionary sector. On the other hand, it seems to be worthwhile to introduce an Telecom Sector in the EMU since we can identify a clearly distinct cluster of telecom firms that is different from the rest of the Communication Services companies. In addition, we observe that the GICS Materials sector seems to substantially misclassify stocks. As in the US case, a large part of this sector seems to be rather heavy industry companies while other companies seem to be more IT or Communication Services driven.

Figure 2 below illustrates for the MSCI USA case the sector clusters according to our correlation-based algorithm compared to GICS' classifications.

Figure 2: Matching of GICS sector and clustering assigned sectors by stock in the MSCI USA universe




*Source: Bloomberg, TOBAM. The estimation period used to create this graph is 01/2016-01/2018.*

From the obtained clusters we can make several observations:

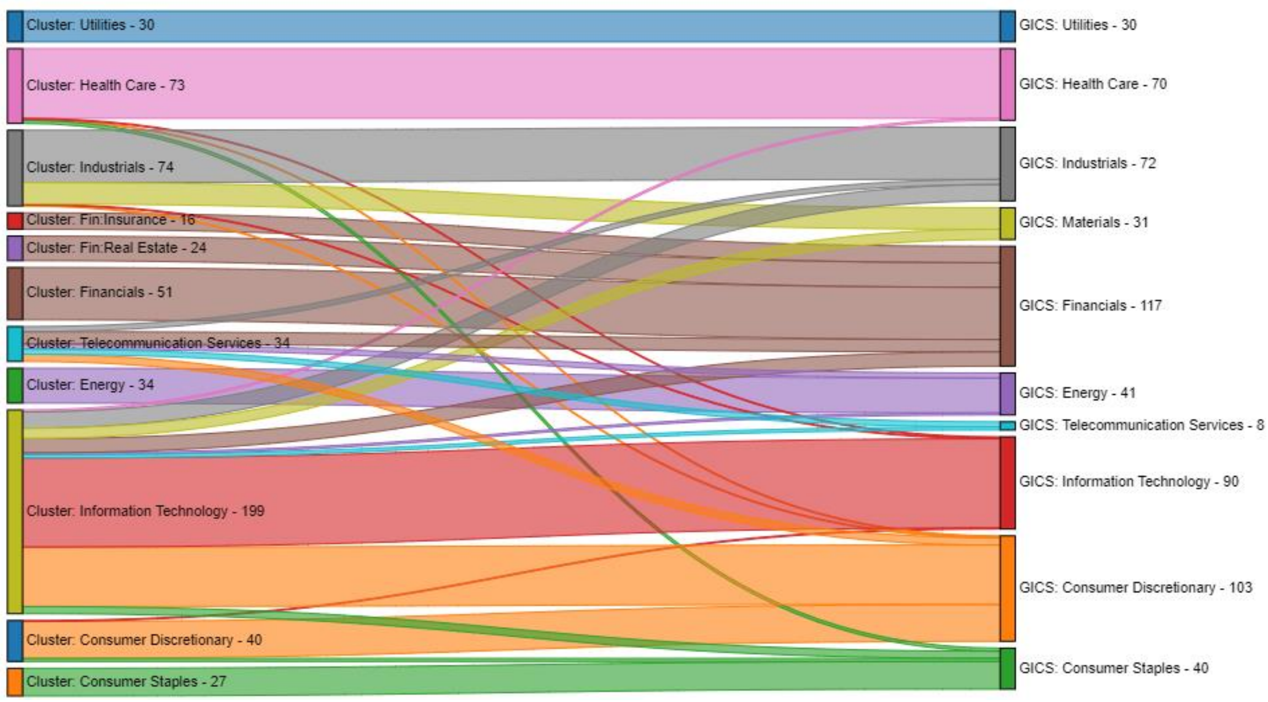
1) The Utilities cluster is perfectly homogeneous and contains all the companies from the MSCI Utilities sector.
2) The Real Estate cluster is perfectly homogeneous and contains most of the Real Estate companies as classified by MSCI except for 4 companies.
3) The Healthcare Cluster contains companies that are all coming from the Healthcare MSCI Sector except for Walgreens Boots Alliance Inc, which is coming from the Consumer Staples MSCI Sector. The company operates retail drugstores that offer a wide variety of prescription and non-prescription drugs as well as general goods. The Company also offers health services, including primary and acute care, wellness, pharmacy and disease management services, and health and fitness explaining why its stock behaves more like a company belonging to the Healthcare sector.
4) The Information Technology (IT) cluster contains companies coming from IT, Healthcare, Communication Services and Consumer Discretionary. The companies belonging to Healthcare are not necessarily misassigned. Indeed, Healthcare Technology companies Cerner Corp and Veeva Systems Inc are examples. The former is a leading supplier of healthcare information technology (HCIT) solutions and tech-enabled services. Hence it is plausible for such company to act as an IT company. The latter offers cloud-based software and mobile apps are used by pharmaceutical and biotechnology companies to manage critical business functions. From the Communication Services sector, we have Alphabet Inc, Facebook Inc, Netflix Inc, Twitter Inc and other similar stocks. Although these stocks are media and entertainment stocks, they rely heavily on software and hardware technology and well as the internet, which makes them act as IT companies. Finally, from the Consumer Discretionary MSCI sector we have Tesla Inc, Amazon.com Inc, but also online services companies such as Expedia Group Inc and Booking Holdings Inc. One potential outlier is Vail Resorts Inc, which is one of North America's leading ski resort operators, managing 35 mountain resorts primarily in the US.
5) The Industrials cluster contains half the companies that are classified by MSCI as industrials and a little less than half the Materials companies.
6) The Communication Services cluster contains various companies from different sectors. First, we get over 67% of the Communication service companies in the cluster and near half the IT companies as well. The IT companies belonging to this cluster deal with connectivity, systems, and networks, such as Motorola Solutions Inc, F5 Networks Inc, QUALCOMM Inc, Cisco Systems Inc/Delaware. IT services companies are also in this cluster (Oracle Corp, Western Union, Accenture PLC, …etc.). This cluster is more likely to be complex and unstable. While it is plausible for a good proportion of companies to belong to this cluster, several outliers are present.
7) Consumer Staples is yet another complex cluster containing companies from various sectors. While most of the companies belonging to Consumer staples are present in the cluster, we can see companies from the Industrials sector. These are all dealing with Aerospace & Defense companies such as Huntington Ingalls Industries. From the industrial sector we group together Environmental & Facilities Services such as Waste Connections Inc and Republic Services Inc. From the IT side, this cluster contain some of the Data Processing & Outsourced Services companies (Automatic Data Processing Inc, Paychex Inc, …etc.)
8) Consumer Discretionary has all the Airline companies from the Industrials sector, three companies from the Consumer Staples: Walmart Inc, Costco Wholesale Corp and Kroger Co who deal with the hypermarket and supermarket activity. The consumer finance companies are all mapped in this cluster.
9) Insurance & Financials: Our model distinguishes the Insurance companies from the financials. There are however stocks that are part of the Financials cluster while being insurance companies such as Lincoln National Corp, MetLife Inc and Principal Financial Group Inc.
10) The Energy cluster contains almost all the companies coming from the MSCI Energy sector and one company coming from the Industrials sector, namely Macquarie Infrastructure, which through its subsidiaries, owns, operates, and invests in a portfolio of infrastructure and infrastructure-like businesses in the US.

### *Advantages of a correlation-based classification approach*

The USA is a very good example because throughout our sample period there have been two major events that can serve as a natural experiment to highlight the complementarity and utility of a correlation-based classification approach compared to a heuristic approach as applied by MSCI. The first is the introduction of the Real Estate sector in 2016 and the second is the 2018 reclassification of several Telecom stocks into Communication Services along with some IT and Consumer Discretionary stocks. In what follows, we exploit these events to study in more detail whether a correlation-based approach would have come to the same conclusions.

We start with the 2016 case, when MSCI promoted Real Estate from being an Industry group within the Financials sector to a Sector on its own. We ran our model between 2013 and 2016 and obtained the results in the below Figure 3. Again, we clearly see that Real Estate and Insurance are distinguished from Financials stocks. This supports the decision made by MSCI with regards Real Estate and is supportive for the Insurance industry to be promoted and become a sector of its own especially since this distinction is persistent over time.

Figure 3: Matching of GICS sector and clustering assigned sectors by stock in the MSCI USA universe for the period 2013-2016




*Source: Bloomberg, TOBAM. The estimation period used to create this graph is 01/2013-08/2016.*

The second case is that in September 2018 the GICS structure was reviewed again by MSCI. The Telecommunication services sector was renamed to Communication Services and now includes some companies from the Information Technology and Consumer Discretionary sectors.

We ran our model in the period between 2015 and 2018 with a reference GICS classification being the MSCI GICS Sectors prior to the 2018 changes. When focusing on IT companies, we can see in Figure 4 that all companies that were part of the IT sector in 2018 and have been moved to either Communication Services, Consumer Discretionary or the Industrials sectors, are still considered as belonging to the IT cluster in our model:

Figure 4: GICS vs our model for stocks that changed their GICS sector from Information Technology in 2018

| Stock Name | Sector 18 | Sector 21 | Model |
|---|---|---|---|
| Activision Blizzard Inc | Information Technology | Communication Services | Information Technology |
| Alphabet Inc | Information Technology | Communication Services | Information Technology |
| Electronic Arts Inc | Information Technology | Communication Services | Information Technology |
| Facebook Inc | Information Technology | Communication Services | Information Technology |
| Leidos Holdings Inc | Information Technology | Industrials | Information Technology |
| MercadoLibre Inc | Information Technology | Consumer Discretionary | Information Technology |
| Take-Two Interactive Software | Information Technology | Communication Services | Information Technology |
| Twitter Inc | Information Technology | Communication Services | Information Technology |
| Zillow Group Inc | Information Technology | Communication Services | Information Technology |
| eBay Inc | Information Technology | Consumer Discretionary | Information Technology |

*Source: Bloomberg, TOBAM. The estimation period used to create this graph is 01/2015-08/2018.*

We argue, based on our predictions, that these stocks act more like Information Technology stocks rather than their actual GICS sectors.

## IV. Conclusion

In this study, we have analyzed and compared models that assign stocks to statistical clusters, based on their returns, and indirectly, using similarities defined as functions of the correlation matrix.

We present criteria allowing to select the best amongst many clustering models, where a key ingredient to this procedure is the closeness to the GICS sector classification. Indeed, it is important to stress that no model is perfect. As such, incorporating GICS sector information that are based on economic grounds to validate a statistical cluster model is reasonable.

Nevertheless, we could highlight in our study that a more quantitatively driven approach that uses directly, what sector classifications should actually represent, i.e., risk exposures, has significant advantages to a purely heuristic approach and could have helped investors to anticipate early on changes in sector classifications that have eventually also been adopted by MSCI. Moreover, our quantitatively driven sector classification would have also overcome the blind spots that are unavoidable for a fundamental approach, that does not measure clear-cut the actual risk drivers that affect prices of different companies.

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