CLASSIFYING NON-BANK CURRENCY SYSTEMS USING WEB DATA

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ABSTRACT

This paper develops a new classification of non-bank currency systems based on a lexical analysis from French-language web data in order to derive an endogenous typology of monetary projects, based on how these currencies are depicted on the internet. The advantage of this method is that it by-passes problematic issues currently found in the literature to uncover a clear classification of non-bank currency systems from exogenous elements. Our textual corpus consists of 320 web pages, corresponding to 1,210 text pages. We first apply a downward hierarchical clustering method to our data, which enables us to endogenously derive five different classes and make distinctions among non-bank currency system and between these and the standard monetary system. Next, we perform a similarity analysis. Our results show that all non-bank currency systems define themselves in relation to the standard monetary system, with the exception of Local Exchange Trading Systems.

KEYWORDS

non-bank money, text mining, web data, downward hierarchical clustering, similarity analysis.

1. INTRODUCTION

What is money? It is particularly difficult to give a clear answer to this question today, as the current surge in various non-bank monetary forms or complementary currencies around the world calls for a re-conceptualization of this economic and social tool. In the literature, money is traditionally defined by its three functions as: (i) a medium of exchange, (ii) a store of value and (iii) a unit of accounting. However, what is exceptional now is the fact that these three functions are combined in one unique national (our supranational) official currency. Indeed, in most previous periods of history, several currencies were used to serve these three functions separately (Douthwaite, 1996; Greco, 2001; Lietaer, 2001, 2013). Hence, complementary currencies are not a new phenomenon. However, since the 1990s, we have seen a massive surge worldwide in the implementation of complementary currencies.

Given the increasing number and complexity of complementary currencies, their puzzling diversity, and their ever-increasing specific features, understanding them is becoming increasingly complex. To understand and better analyze their impact and to better manage and support their development, it is necessary to establish a clear classification of them. In particular, Place & Bindewald (2015) argue that typologies are needed in order to "appropriately evaluate CCS against their own and diverse targets and not against implicit notions of success or ambition" (p.155). In this regard, the literature on complementary currency classification, initiated by Kennedy & Lietaer (2004) and Bode (2004), currently represents a rapidly-growing research field (see, Blanc, 2011, 2013; Schroeder, 2011; Slay 2011; Martignoni, 2012; Bindewald et al., 2013; Seyfang & Longhurst, 2013). Overall, authors deal mainly with questions such as, what kinds of exchange do CCS aim at promoting? Between whom? For what purposes?

Bode (2004) suggests a classification of complementary currencies according to the following two criteria: (i) their compensation schemes and (ii) the type of co-contracting parties involved. Within this typology, he further distinguishes between "services-based complementary currencies" and "monetary-based complementary currencies". Here, we notice a clear dividing line between barter clubs and other Local Exchange and Trading systems (LETS), independent from standard moneys, and citizens' currencies, anchored to national or supranational currencies. Kennedy & Lietaer (2004) propose a more detailed and complex typology, including technical features of complementary currencies and define five main classification factors: (i) the objectives they serve, (ii) their functions, (iii) their medium of exchange, (iv) their underlying process of monetary creation and (v) their cost recovery schemes. Starting from this basis, the current evolution of this literature aims at clarifying and deepening these initial classifications by accounting for a larger set of characteristics (see Blanc, 2011; Martignoni, 2012; Seyfang & Longhurst, 2013; Bindewald et al., 2013; Place & Bindewald, 2015).This has resulted in ever more complex and varying classifications, making standard comparisons more difficult.

Indeed, Derruder & Lepesant (2011) and Dittmer (2013), mainly divide complementary currencies according to their objectives (characterized from a microeconomic point of view and a meso/macroeconomic point of view, respectively), Bindewald et al. (2013) put forward a typology of complementary currency systems based on four categories, namely (i) political, (ii) economic, (iii) social and (iv) environmental, which are then subdivided according to their respective scope (meta, macro, meso and micro). Place & Bindewald (2015), also subdivide the « political » category into two further distinct categories, namely "culture" and "governance".

Seyfang & Longhurst (2013) define a classification of 3,428 monetary projects from 23 countries located across 6 continents. Their sources come from the compilation of existing database and field information. In order to classify these projects, they assume that three distinct types of monetary projects appear in the literature: (i) credit services, (ii) mutual exchange systems and (iii) local currencies. They then add a fourth category, namely (iv) barter clubs. According to the authors, the first two classes, credit services and mutual exchange systems, make up 91.5% of all recorded initiatives, whereas barter clubs only account for 1.4% of monetary projects in their database. Therefore, local currencies and barter clubs seem to account for a very limited number of complementary currency systems around the world, unless this observation comes from a bias arising from the database itself or from the classification method used by the authors. Indeed, we believe that the authors' choice to differentiate between barter clubs and mutual exchange systems is questionable. When we look at the definitions the authors provide for these two categories, they seem to be nearly equivalent, the authors' decision to separate them ap-

pears to be based only on the fact that the projects call themselves "barter clubs" or "mutual exchange systems", and not based on significant difference between the two in terms of functioning, structure and goals.

This demonstrates an example of the current trend in the literature, which seems to be in search of an increasing number of complementary currency features, with ever more complex division into sub-fields. We believe that these developments make the understanding of complementary currencies projects trickier, and that such complex classifications gradually lose sight of their goal of simplification and clarification of a given phenomenon.

On this point, Blanc (2013), acknowledges the relative failure of the literature to define a clear-cut typology of complementary currencies, and we believe that following the current trend of increasing classification criteria will only worsen this failure to find a useful classification system.

First, the problem lies in the fact that authors do not seek to classify the same currency systems. Some authors want to account for all existing currencies, whereas others want to account for only a limited set, depending on the authors' interests. According to Blanc (2011), the current heterogeneity of complementary currencies is so great that resorting to at least several classifications becomes unavoidable. Moreover, Blanc (2011) argues that? the literature's difficulty in defining a clear and efficient typology of complementary currencies may come from an exclusive focus on moneys, when the emphasis should instead be placed on systems.

As a result, Blanc (2011) suggests a classification based on systems rather than on objects and determines three main classes of systems: (i) local currencies (territorial/geographical-based projects), (ii) community currencies (originating from preexisting communities) and (iii) complementary currencies (economic-based projects focused on production and exchange activities into markets). Going one step further by broadening his previous analysis, Blanc (2013), drawing upon Polanyi's works, proposes a typology of monetary projects according to three "ideal types": (i) public currency, (ii) profit-making currency and (iii) citizens' currency, and six subcategories (state, sub-state, market, captative, community and trade). This taxonomy has the clear advantage of enabling the classification of all types of currencies, with the only exception being that of crypto-currencies. In our view, this typology is the most successful to date.

As evidenced in the brief literature review above, classification of complementary currencies is clearly a thorny issue and a clear-cut typology has not yet been found. We believe that the issue of classification seems to resist resolution because the purpose of classification is not clear enough. We believe that clarity can be found in answering the following questions: (i) Which elements do authors need to focus on and why?; (ii) How do databases on complementary currencies get compiled? On the one hand, authors have focused on different aspects of monetary objects or projects such as their functioning, the actors they involve, the types of goods and services exchanged their conditions, their medium of exchange and the goals they serve. Although these various elements are strongly interrelated, each author inevitably favors some particular features of monetary projects he believes more significant and representative and subdivides each element accordingly, which makes the existing classifications very hard to compare. Furthermore, databases on complementary currencies are still poorly organized and their availability is limited. As a result, it proves very challenging to form an exhaustive and representative database, which further complicates the classification of complementary currencies according to their characteristics. Since authors resort to different and partial databases, they obviously find different results.

In order to circumvent these problems, we believe that a relevant way to classify complementary currencies may be to resort to a classification based neither on recorded objective data nor according to a priori factors, but instead to endogenously categorize the largest possible set of monetary projects using web data. Indeed, the internet abounds in articles, blogs and other web content dedicated to complementary currencies. This combined web content represents an invaluable source of information on complementary currencies despite the fact that it is in textual form rather than statistical. Yet, for more than two decades, there has been an important development in statistical methods for text analysis, especially regarding endogenous classification of textual corpora according to their content. A clear benefit of this methodology is that it neither resorts to a priori hypotheses about factors driving the typology, nor focuses on specific subsets of monetary projects. In our case, a larger sample size of data related to complementary currencies would especially mitigate the issue of data-bias author preferences and lead to a more objective classification. Furthermore, even if there is possible ideological bias in sources that discuss complementary currencies, by gathering many different sources dealing with this topic, our methodology offers a

way to derive a more representative discourse on complementary currencies. Hence, we use the term "non-bank" to qualify most of the existing currency systems. We acknowledge that the choice to base our study on French lexical data reduces the scope of our study and thus the external validity of our classification. However, we believe that focusing on lexical data available in French provides a first test to gauge the relevance of our methodology in deriving a new classification of complementary currencies. Obviously, further research needs to be done to extend our work to other languages, such as English, Spanish, Portuguese or German, in order to allow lexical comparisons between monetary projects according to their geographic origins or the language used to depict them.

The rest of this paper is organized as follows. Section 2 presents our lexical corpus data, as well as our statistical methodology. Section 3 displays the main results regarding the endogenous classification of non-bank currencies using a top-down hierarchical clustering. Section 4 explores the relationships between the various estimated classes in Section 3 using a similarity analysis, and Section 5 concludes.

2. METHODOLOGY

According to Gerin-Pace (1997), statistical methods for text analysis were born in the 1980s and since that time they have followed two main development paths: a first set of methods aims at analyzing writing style (text comparison and evolution), while a second set deals with the analysis of the meaning of a given textual corpus. Our paper draws upon this latter set of methods.

2.1. The design of the textual corpus

We initially set 38 French keywords related to the term "complementary currencies". We chose to keep 10 web page results for each keyword, so as to end up with a textual corpus of around 300 web pages. Our raw data then underwent three types of "cleaning" procedures. First we procedure tested Google search results for each keyword. Here, we chose to withdraw a given keyword from our initial list if: (i) its first ten URL results gave webpages not related to complementary currencies or (ii) its URL results were exactly the same as some other keywords in the list. Consequently, our textual corpus does not include duplication webpages, and subpages of the same main domain name do not count as individual pages. The second "cleaning" procedure dealt with the selection of data collected from the extracted webpages. We chose to focus only on webpages that included informative data directly available in a textual form on each webpage we extracted. As a result, we dropped multimedia URLs (for instance, links to videos and radio programs), homepages without any informative content, and finally URLs related to translated webpages. Likewise, in order to keep our textual corpus balanced, we chose to drop URLs that linked to pdf files. Moreover, we also canceled URLs that referred to books (for example, e-commerce sites, Google books and editor webpages). Therefore, our textual corpus is constituted from four main sources: (i) newspapers and magazines, (ii) blogs, (iii) free online encyclopedias and (iv) webpages from different actors of complementary currency systems. Finally, the third "cleaning" procedure was based on the extracted webpages themselves and consisted in keeping only text data from each webpage (i.e., we dropped web navigation terms such as tags, signs and pictures). We additionally removed internet user comments, since they were often extremely long and so risked skewing the amount of extracted text for each keyword.

In the end, our textual corpus includes 320 webpages from the extraction of the URLs of the first ten Google search results associated to each of the 32 final French keywords used to depict non-bank currency systems.

2.2. Descriptive statistics of the textual corpus

Our textual corpus is made up of 320 distinct webpages. Starting from this raw data, we resorted to a corpus lemmatization in order to reduce vocabulary diversity and better emphasize semantic proximities between words. This method can be viewed as a way to "undress" words from their grammatical shape, so as to gather them into one family. For instance, all conjugations of the verb "have" (avoir) will be combined into the same lemma "have" (avoir). This seems to be especially relevant in our context, since we are only interested in the informative content of texts and not in form.

Furthermore, when processing lexical data, we divided our final textual corpus into segments of 20 consecutive words after lemmatization. Consequently, the final partition of our corpus is the following:

- 320 Initial Context Units (ICU).

- 17,939 Elementary Context Units (ECU), also called text segments, which represent subsets of 20 successive words in a given ICU.

- 359,223 words and 22,369 words after lemmatization (i.e., distinct terms).

Appendix 2 gives the 50 most frequent words in our corpus, with their respective total frequency. Since webpages were extracted with keywords including the term "currency", it seems logical that this term is the most frequent word found in our corpus, with 4,733 occurrences. The three next most frequent terms are "exchange" (1,569 occurrences), "local" (1,443 occurrences) and "system" (1,314 occurrences).

2.3. Downward hierarchical clustering and similarity analysis

2.3.1. Downward hierarchical clustering

In order to implement our downward hierarchical clustering, we apply the Reinert's (1983, 1990) ALCESTE (Analyse des Lexèmes Cooccurrents dans un Ensemble de Segmentation du Texte Etudié) method using IramuteQ software. Downward hierarchical clustering (henceforth DHC) is an algorithm, which starts by assuming that all words in a corpus belong to the same category. For each algorithm iteration, we derive the two most distinct categories of words. This iterative process stops when the extracted variance is not improved by a new partition of data. From this perspective, the final number of classes is left a priori undetermined, which in our case is especially relevant for deriving an endogenous classification of non-bank currency systems without ex ante hypotheses.

Once we have divided our corpus into k classes, we need to determine features related to each estimated class, which entails analyzing the words included in each class and especially the contribution of each word j to a given class k. For this purpose, we use a Chi-square statistic, to assess the extent of connection between each word and each class. From these estimated connections, the use of a Factor Component Analysis (henceforth FCA) enables us to characterize similarities and oppositions between estimated classes by pooling them into factors that delimit their respective outlines.

Note that it is possible to implement a DHC on texts (each webpage is processed as a whole), on simple segments (fractions of a given text), or on pooled segments (gathering of text fractions). Our classification tests based on texts were inconclusive, since the estimated classes were somewhat dispersed and uninformative. This is because most webpages contain several topics, so that considering a webpage as a whole does not make sense from a semantic point of view. Therefore, text partitioning into segments turns out to be essential in order to carry out an efficient text analysis. Our classification tests based on simple text segments proved to be more significant. However, one obvious requirement here is to define the length of segments to be considered. When importing a corpus, IramuteQ offers different types of segmentations, based either on the number of successive words needed to be considered or based on signs or paragraphs. In our case, a classification based on the number of successive words seemed to be the most appropriate, given that webpages are not necessarily structured by paragraphs and classification based only on words would not make sense. We did several tests for different segment sizes (40, 30, 20 and 10 words), and the most clear-cut results were obtained from a classification based on 20 successive words, although few discrepancies appeared between classifications based on 20 and 10 successive words. However, classification with more than 30 words led to poorer results, indicating that longer segments include too much heterogeneous information and make classification less efficient.

Lastly, we implement a DHC for both simple segments and pooled segments. Classification leading to the most convincing results is based on pooled segments, which consist of a two-part classification. In a first step, we specify a given number of words to be pooled and then a DHC is applied to the segments in order to keep the pooling of segments, which maximizes the variance extracted from words included in each segment. In a second step, a DHC is applied to pooled segments in order to derive our final estimated classes. As a result we are able to gather similar segments in terms of included words before resorting to the estimation of the k classes. With this method, the

estimated classes are much more cohesive and significant than those obtained on simple segments, which is logical since the final classification is derived from groups of words generated according to their proximity and not only according to a given size of successive words (as in classification on simple segments). Hence, we chose to keep classification estimates obtained through the implementation of a DHC on pooled segments of 20 occurrences.

2.3.2 Similarity analysis

Similarity analysis measures distances between different semantic territories. In our case, this identification work is required if we want to highlight differences or similarities in the relationship between lexical representations of money. Therefore, after implementing our DHC, we undertake identification of semantic categories in an attempt to gauge the distance between the k estimated classes. Indeed, although DHC enables us to endogenously estimate a given number of classes according to specific features, it is not able to depict either the relationship between close semantic territories or combinatory territories between several classes.

To assess distances between semantic territories, we chose to work with a method from applied graphs theory. This method, based on Blondel et al. (2008) and Lambiotte et al. (2009), allows us to depict nodes and links from a modularity calculation in order to statistically determine groups of nodes (in this case semantic continents) that gather several nodes and share common features. As a result, we are able to endogenously identify central and peripheral entities in a given graph containing lexical data. In this case, a node is said to be central when most of the possible paths that connect the graph pass through the node. Here, the Betweeness Centrality algorithm from Brandes (2001) allows us to compute the node, through which most of the possible paths in the graph pass. In terms of interpretation, the closer a node is to the center of the graph, the more central it is for the definition of non-bank currencies. Conversely, nodes further away from the center of the graph are more peripheral to the definition of non-bank currencies. When applied to lexical data, this centrality algorithm leads to the identification of reference classes, i.e., classes which serve as the origin point (or center of gravity) for the definition of other classes.

3. RESULTS FROM THE DOWNWARD HIERARCHICAL CLUSTERING

When first applying a DHC to our corpus using IramuteQ, we derived 5 classes. The following dendrogram helps to better visualize this result:

Graph 1. Dendrogram
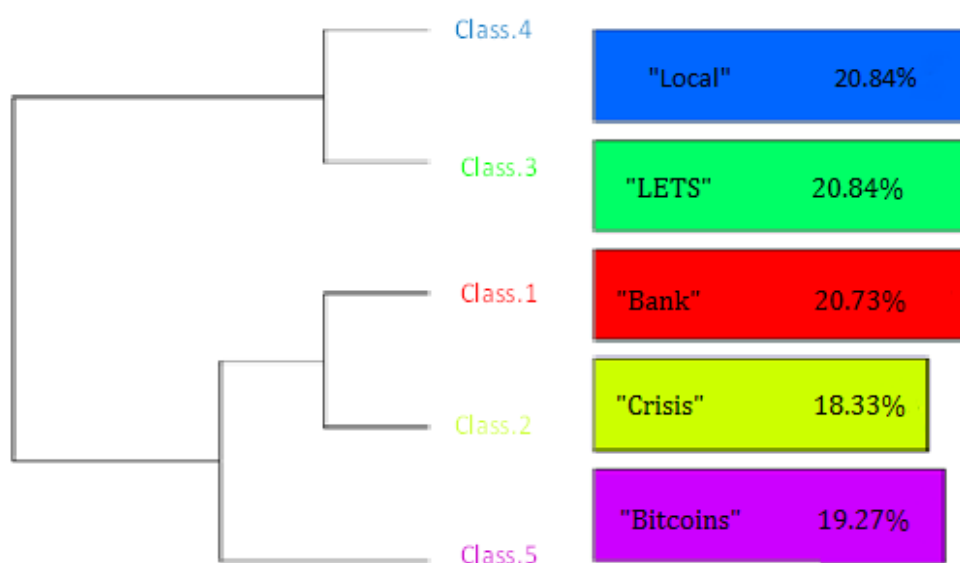
This dendrogram shows that our five estimated classes are well balanced in terms of the text segments they respectively include, since each of them covers around 20% of all segments. In order to see which classes have been endogenously created, we now analyze the lexical content of each of them. Table 1 below gives the 20 most specific terms from each estimated class (according to their Chi-square statistic).

**Table 1. The 20 most specific terms of each estimated class**

Class 1. "Bank"	Class 2. "Crisis"	Class 3. "LETS"	Class 4. "Local"	Class 5. "Bitcoins"
% of segments : 20.73	% of segments: 18.33	% of segments: 20.84	% of segments: 20.84	% of segments: 19.27
Bank **(Banque)**	Crisis (Crise)	LETS (SEL)	Local (Local)	Bitcoin (Bitcoin)
Value **(Valeur)**	Global (Mondial)	Accorderie (Accorderie)	Project (Projet)	Transaction (Transaction)
Money **(Monnaie)**	Economist (Economiste)	Exchange (Echange)	Sol (Sol)	Virtual (Virtuel)
Banknote **(Billet)**	Bernard Lietaer (Bernard Lietaer)	Barter (Troc)	Solidarity (Solidaire)	Crypto (Crypto)
Issue **(Emettre)**	Monetary (Monétaire)	Service (Service)	Citizen (Citoyen)	Payment (Paiement)
Price **(Prix)**	Capitalism (Capitalisme)	Member (Membre)	Social (Social)	Satoshi Nakamoto (Satoshi Nakamoto)
Debt **(Créance)**	Reform (Réforme)	Network (Réseau)	Violet[i] (Violet)	Electronic (Electronique)
Contract **(Contrat)**	Inflation (Inflation)	Club (Club)	Association (Association)	Card (Carte)
Free **(Libre)**	Country (Pays)	Accorderies (Accorderies)	Economy (Economie)	Bloc (Bloc)
Monetary **(Monétaire)**	People (Peuple)	Adherent (Adhérent)	Territory (Territoire)	Mining[ii] (Minage)
Reserve **(Réserve)**	War (Guerre)	Accordeur (Accordeur)	Complementary (Complémentaire)	User (Utilisateur)

Mass **(Masse)**	Depression (Dépression)	REN[iii] (RERS)	Toulouse (Toulouse)	Software (Logiciel)
Credit **(Crédit)**	Communism (Communisme)	Skill (Compétence)	Development (Développement)	Register (Registre)
Circulation **(Circulation)**	Politics (Politique)	Argentinian (Argentin)	MLC (MLC)	Publish (Publier)
Private **(Privé)**	Big (Grand)	Offer (Offrir)	Service provider (Préstataire)	MTGOX (MTGOX)
Case **(Cas)**	Cause (Cause)	Quebec (Québec)	Charter (Chartre)	Platforms (Plateformes)
Fonte **(Fonte)**	Current (Actuel)	Exchange (Echanger)	Firm (Entreprise)	Computer science (Informatique)
Valorimeter[iv] **(Valorimètre)**	Poor (Pauvre)	Know-how (Savoir-faire)	Regional (Régional)	Decentralize (Décentraliser)
Central **(Central)**	Population (Population)	Reunion (Réunion)	Ethical (Ethique)	Calculation (Calcul)
Melting **(Fondant)**	Society (Société)	Mutual (Réciproque)	Sustainable (Durable)	Computer (Ordinateur)

We chose to name each class after the most representative word according to the Chi-square statistic, i.e., the first word in each column. Class 1 or "Bank" can be interpreted as depicting the traditional representation of the standard monetary system since we find large quantities of vocabulary depicting monetary creation, banks, currencies and their uses. This is not surprising since this class is the result of the representation of the standard monetary system by web sources related to non-bank currencies. Class 2 or "Crisis" can be viewed as referring to the recent financial and economic crisis, and contains many terms related to its causes and consequences. This result is especially interesting as it supports previous works that emphasize the countercyclical dimension of complementary currencies (Lietaer, 2012, 2013; Herlin, 2012, 2015). As such, non-bank currencies are clearly defined in our corpus as an alternative way to deal with the consequences of financial and economic crises. For instance, recent experiments, such as in Europe (e.g., France, Germany and Belgium) and Latin America (Argentina and Brazil), and older experiments like the Swiss's WIR during the Great Depression of the 1930's, show that surges in complementary currencies often arise in troubled financial and economic times during which people have less access to liquidity. Class 3 or "LETS" depicts Local Exchange and Trading systems (LETS) and barter clubs and refers to all currencies that represent ways of directly exchanging goods or services between people, without resorting to intermediaries, such as accorderies, LETS, or REN (Reciprocal Exchanges Networks). As a result, these organizations operate outside the traditional market system. Class 4 or "Local" can be interpreted as describing social money projects located in a specific territory and based on ethical and social values. These projects are distinct from the LETS category since they are used like traditional money on the market system (meaning they do not have price mechanisms such as timebanks). Finally, Class 5 or "Bitcoins" is clearly related to virtu-

al currencies, of which bitcoin is hands down the most well-known representative. In this class, the most recurrent vocabulary deals with references associated to virtual moneys.

Graph 2. Factor Component Analysis of the classified segments
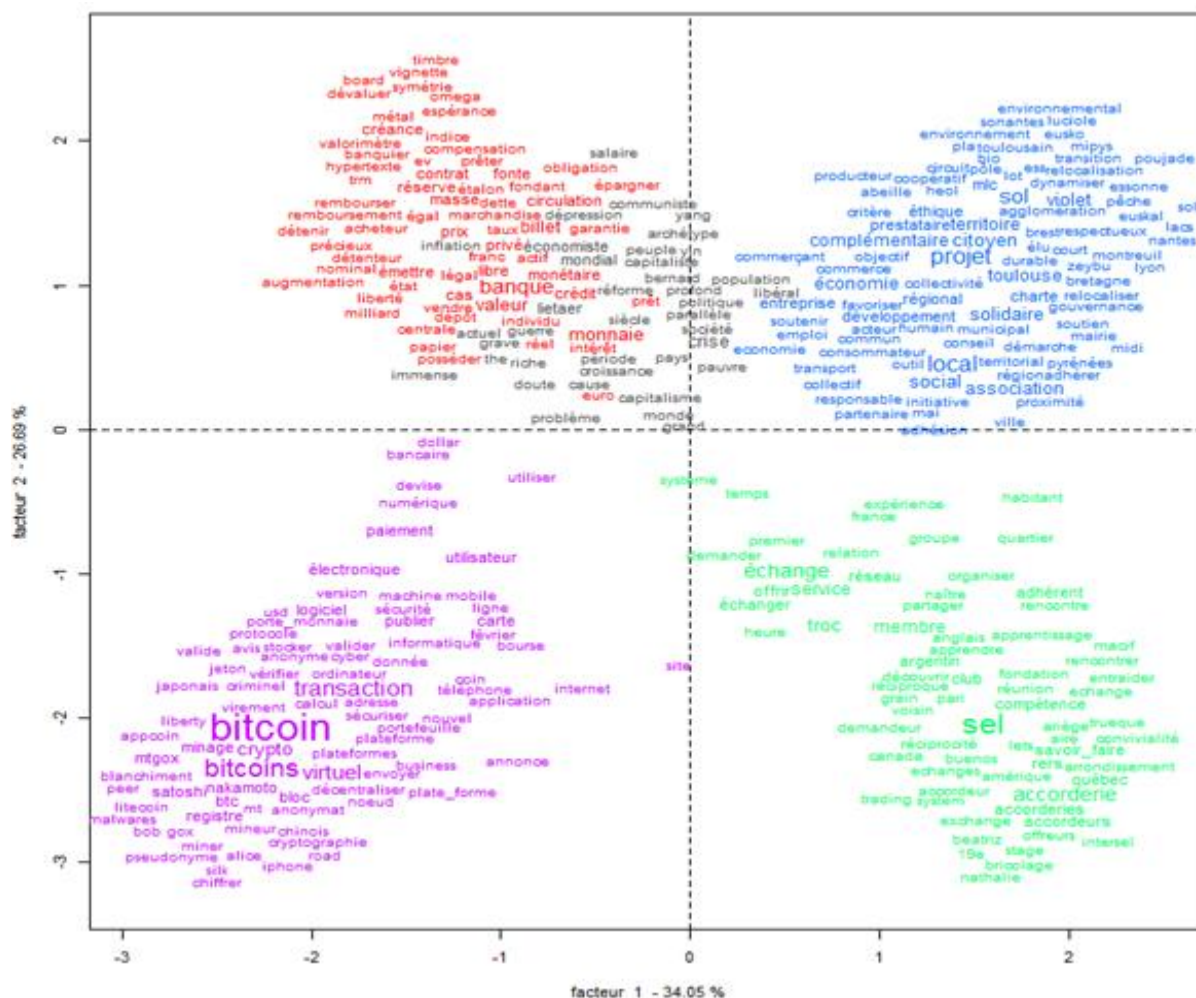
Now, we need to go one step further and study which precise components drive the separation between these five estimated classes in order to derive classification criteria at the root of non-bank currency systems. To this end, we use a Factor Component Analysis (henceforth FCA), which enables us to interpret factors that gave rise to our DHC classification. Given that the first two factors are those that contribute most to our classification (together they account for 61% of the total variance in our data) and are also the most meaningful in terms of class division, we focus our interpretation on these two factors only. In order to get better insight on the distribution of our five estimated classes according to Factors 1 and 2, as well as their respective distance to these factors, Graph 2 shows Factor 1's values on the horizontal axis and Factor 2's values on the vertical axis. Each class is depicted with a specific color, and words that belong to each class are located according to their respective coordinates in Factor 1 and 2.

Graph 2 clearly shows that Classes 1 "Bank" (in red, in the upper left) and 2 "Crisis" (in black, top center) are closely related to each other, whereas Classes 4 "Local" (in blue, upper right), 5 "Bitcoin" (in purple, lower left) and 3 "LETS" (in green, lower right) are opposed to Classes 1 and 2.

Classes 1 and 2 appear to be embedded in each other. This result seems logical since they correspond to the standard monetary system and the recent financial and economic crisis, respectively. As a result, local currencies stand out from the standard monetary system through Factor 1, but are linked together through Factor 2. Moreo-

ver, it is worthwhile to note that Class 2, which refers to the recent financial and economic crisis, reflects a link between standard moneys and social moneys. Indeed, since the perceived failure of the standard system in times of crises usually gives rise to a surge in social money systems, it seems relevant to see Class 2 located in between Classes 1 and 4, which are associated to the standard monetary system and local currencies, respectively. Class 3 (LETS) appears to be the most distant class from the standard monetary system, differentiating from it through both Factors 1 and 2. Finally, Class 5 (Bitcoin) and Class 4 (Local currencies) are the two next most opposing classes. Putting together these results, it is therefore possible to derive the meaning of the two factors behind our five estimated classes.

When we look at Graph 3, the implementation of the FCA shows that Classes 1 "Bank" and 2 "Crisis" with respect to Class 4 "Local", as well as Class 3 "LETS" compared to Class 5 "Bitcoin" are opposed to each other through Factor 1. As a result, Factor 1 enables us to distinguish local moneys from standard moneys, as well as bitcoin and other crypto-currencies from LETS and barter clubs. Therefore, Factor 1 could be interpreted as depicting the objectives and values of existing moneys, whether (i) profit-making and speculative (negative values of Factor 1), or (ii) social (positive values of Factor 1). On the other hand, Graph 3 also points out that Class 3 and Class 5, compared to Classes 1, 2 and 4, are opposed to each other through Factor 2. As a result, Factor 2 enables us to distinguish standard and local money from LETS and bitcoins and can be interpreted as a separation factor based on a more functional criterion, namely the anchoring to national or supranational moneys. Indeed, to our knowledge, the similarity between bitcoins and most of the LETS and barter club currencies is their independence with respect to national or supranational currencies. As a result, negative values of Factor 2 are related to independence from national or supranational currencies, i.e., monetary creation outside any anchoring to standard money, whereas positive values correspond to reliance on national or supranational currencies.

Consequently, by pooling results from the implementation of a DHC to our lexical corpus, we have endogenously derived two structural features of non-bank currency systems that enable us to classify most existing currency systems in a rather simple way. Table 2 below gives our resulting classification of non-bank currencies.

Table 2. Classification of non-bank currencies

		Goals/values	
		Profit/commercial value	Non profit/social value
Dependency	Dependent on standard currencies	National and supranational legal currencies	Complementary local currencies, citizens' currencies, social currencies
	Independent from standard currencies	Transaction currencies like bitcoin, crypto-currencies	LETS, barter clubs, accorderies, Reciprocal Exchange of Knowledge Networks

Table 2 allows us to make some interesting conclusions. First, local currencies seem to largely contest standard money values (speculation, concentration of wealth; see Blanc, 2013). Thus, it makes sense that these currencies are in opposition on this issue, while still linked to standard money, owing to their convertibility in national or supranational currencies and to their monitoring by monetary authorities. Furthermore, local currencies are completely in opposition to cryptocurrencies, not only with regard to their respective values, but also in terms of dependence with respect to standard moneys bitcoin being independent from the standard monetary system. However, we can see that virtual currencies share common goals associated with standard moneys such as profit seeking, speculation and wealth accumulation.

As we have already seen with Graph 2, LETS and barter clubs most strongly oppose standard monetary projects. They share with virtual currencies the feature of not being reliant on the standard monetary system. Nevertheless, LETS and barter clubs are distinct from cryptocurrencies in terms of their respective values, since barter clubs advocate social, mutual, ethical and environmental values, whereas cryptocurrencies do not.

Finally, one additional interesting feature of our results is that they strongly echo Blanc's (2013) complementary currencies classification. Indeed, like the author, we find the same partition between LETS and barter clubs on one side and local currencies on the other and surprisingly, according to the same criteria. However, contrary to Blanc (2013), our typology does not enable us to differentiate between public and profit-making moneys within the standard money class. This could stem from a lack of data regarding this class in our corpus as well as from the limitation of our methodology itself in finding more classification criteria in a given set of lexical data. Yet, our classification accounts for cryptocurrencies while Blanc's (2013) classification does not.

4. SIMILARITY ANALYSIS RESULTS

In this section, we go one step further and perform a similarity analysis in order to better understand the outlines associated to our five previously estimated classes, including their semantic similarities and discrepancies. To do this, we draw upon the lexicometrical literature dealing with the distance measurement between lexical fields from different documents.

Graph 3. Semantic community detection using similarity analysis
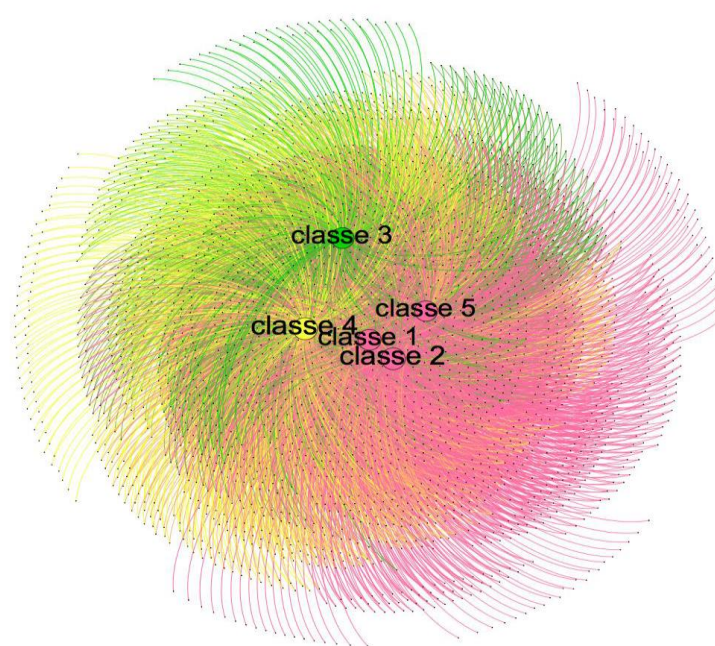
Graph 3 displays the results. First of all, we notice that the estimated relationships between classes show that Class 1 "Bank" is at the center of this graph, hence representing the center of gravity of the other classes. Further-more, this statistical method allows us to identify three distinct lexical "continents". The first two continents related to Classes 3 "LETS" and 4 "Local" are mono-classes. However, Classes 1 "Bank", 2 "Crisis" and 5 "Bitcoin" belong to the same continent. We can therefore interpret results from our similarity analysis in the following way: (i) banking moneys are the center of gravity, the central semantic reference to non-bank currencies. This reference might therefore justify the denominations "complementary currencies" or "non-bank currencies", since these two terms rely on a similar reference norm: standard money; (ii) only LETS currency types appear not to be reliant on this reference to standard money, as they are farthest away from the center of the graph; (iii) "cryptocurrencies", "crisis" and "standard money" classes belong to the same semantic community and, therefore, potentially to the

same system of values and social representations. This result can also be interpreted as a semantic oppositional expression formulated by people's knowledge stemming from local or complementary currency projects. Indeed, currency systems define themselves in reaction to behaviors and values associated to the standard monetary system. In addition, we can further extend this remark to currencies related to Class 3.

5. CONCLUSION

This paper offers a new classification of non-bank currency systems based on a lexical analysis from French-language web data. Starting from the observation that it is often difficult to access exhaustive and factual data on complementary currencies, we attempt to circumvent this drawback by using lexical web data as a source. In light of the recent literature, the classification of existing complementary currencies clearly appears to be a thorny issue and has not yet succeeded in finding a clear-cut typology (see also Blanc, 2013). From our point of view, the existing classifications are very hard to compare because authors focus on different monetary objects or systems, favor some specific features of projects they believe more significant and representative and carry out their own subdivisions within each classification.

In order to avoid these pitfalls, we built a vast lexical corpus covering the largest possible set of these new monetary objects and then resorted to an endogenous classification method, enabling us to identify structural factors behind our lexical data. The corpus was created from 32 French-language keywords that referred to complementary currencies. We kept the first 10 URL results for each Google keyword search and then extracted their respective content. As a result, our corpus is made up of 320 webpages, corresponding to 1,210 text pages and 342,585 words or 17,939 segments of 20 successive words.

In the first step we ran a downward hierarchical clustering (DHC) on text segments. This algorithm recursively finds the best way to divide data into cohesive groups and derives the optimal number of monetary project classes. Next, the implementation of a Factor Component Analysis (FCA) allowed us to determine the latent factors behind the previously DHC estimated classes. This classification method enabled us to derive 5 consistent and significant classes from our lexical corpus: (i) standard currencies, (ii) the recent financial and economic crisis, (iii) local currencies, (iv) LETS and barter clubs and (v) cryptocurrencies. One clear advantage of this method is that it neither resorts to a priori hypotheses about factors driving the typology nor focuses on specific subsets of monetary projects. Indeed, by using a larger sample size of data related to complementary currencies, our methodology mitigates the issue of data-bias author preferences and leads to a more objective classification. However, even if there is a possible ideological bias in most sources that discuss complementary currencies, our methodology, by gathering many different sources dealing with this topic, offers a way to derive a more representative discourse on complementary currencies. Our results lead to a simple and clear classification of most existing current monetary forms and uncover two fundamentals sources of differentiation between them, namely: (i) dependence on or independence from national or supranational currencies and (ii) values and goals behind monetary projects. Finally, the implementation of a similarity analysis allowed us to better understand the outlines associated to our five estimated classes and their semantic similarities and discrepancies. Results derived from this method show that, except for LETS and barter clubs, all new monetary forms define themselves with respect to the standard monetary system. We believe that our results are a valuable contribution to the existing literature, in particular, because typologies are useful to appropriately evaluate CCS against their own and diverse targets, as underlined by Place and Bindewald (2015). Our results allow us to classify all CCS according to two very simple criteria and should lead to the development of only three different evaluation models. Moreover, since our results strongly echo theoretical classifications from Blanc (2013), our paper can be viewed, to a certain extent, as an empirical test of his non-bank currencies typology.

We acknowledge that this paper has focused only on French lexical data. Hence, one relevant extension of this work would be to apply the same approach and methodology to other languages, such as English, German and Spanish, so as to foster lexical comparisons between monetary projects according to their geographic origins and/or the language used to describe them.

Finally, we believe that this paper opens a new methodological field of research by showing the possibility of deriving relevant typologies from various economic or social phenomena through the analysis of lexical data from the internet. Consequently, beyond our conclusions relative to non-bank currencies, we hope that this paper will contribute to the increased diffusion and use of textual statistics in economic and social studies.

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APPENDIX

Table 1. Final keywords used to extract web data

1. Complementary currency (Monnaie complémentaire)	9. Depreciating money (Monnaie fondante)	17. Cyber money (Cyber monnaie)	25. Monetary innovation (Innovation monétaire)
2. Regional currency (Monnaie régionale)	10. Unofficial money (Monnaie parallèle)	18. Global money (Monnaie mondiale)	26. Accorderie (Accorderie)
3. Local currency (Monnaie locale)	11. Alternative money (Monnaie alternative)	19. Time bank (Banque de temps)	27. Local Exchange System (Système d'échange local)
4. Complementary local currency (Monnaie locale complémentaire)	12. Fair money (Monnaie equitable)	20. Time money (Monnaie temps)	28. Proximity Exchange Systems (Systèmes d'échanges de proximité)
5. Community currency (Monnaie communautaire)	13. Ethical money (Monnaie éthique)	21. Cryptocurrency (Crypto-monnaie)	29. Universal Exchange Garden (Jardin d'échange universel)
6. Social currency (Monnaie sociale)	14. Electronic money (Monnaie électronique)	22. Local Exchange and Trading Systems (Systemes d'échanges locaux)	30. Barter system (Système de troc)
7. Solidarity currency (Monnaie solidaire)	15. Virtual money (Monnaie virtuelle)	23. Reciprocal Knowledge Exchange Networks (Réseaux d'échanges réciproques des savoirs)	31. Inter-firm compensation system (Système de compensations inter-entreprises)
8. Free money (Monnaie libre)	16. Digital money (Monnaie numérique)	24. Barter clubs (Clubs de trocs)	32. Supplementary currency (Monnaie supplémentaire)

Table 2. The 50 most recurrent terms in the lexical corpus with their respective frequency

1. Currency [4733] (Monnaie)	11. Value [702] (Valeur)	21. Euro [551] (Euro)	31. To use [426] (Utiliser)	41. Credit [339] (Crédit)
2. Exchange [1569] (Echange)	12. Network [679] (Réseau)	22. Barter [547] (Troc)	32. Electronic [419] (Eléctronique)	42. Exchange [329] (Echanger)
3. Local [1443] (Local)	13. To enable [650] (Permettre)	23. Project [526] (Project)	33. Association [398] (Association)	43. New [321] (Nouveau)
4. System [1314] (Système)	14. Bitcoin [650] (Bitcoin)	24. Firm [477] (Entreprise)	34. Big [391] (Grand)	44. Website [319] (Site)
5. Bank [885] (Banque)	15.Complementary [648] (Complémentaire)	25. France [471] (France)	35. Payment [385] (Paiement)	45. Member [319] (Membre)
6. Monetary [863] (Monétaire)	16. Article [617] (Article)	26. Money [466] (Argent)	36. Solidarity [383] (Solidaire)	46. Banknote [319] (Billet)
7. Service [820] (Service)	17. Time [604] (Temps)	27. To see [462] (Voir)	37. Transaction [365] (Transaction)	47. Activity [316] (Activité)
8. Social [792] (Service)	18. Economic [569] (Economic)	28. Account [439] (Compte)	38. Market [363] (Marché)	48. Society [315] (Société)
9. LETS [777] (SEL)	19. To create [568] (Créer)	29. Financial [438] (Financier)	39. Country [360] (Pays)	49. Example [315] (Exemple)
10. Economy [720] (Economie)	20. To put [554] (Mettre)	30. First [432] (Premier)	40. World [355] (Monde)	50. To offer [314] (Offrir)

ENDNOTES

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[i] We did not translate the French word « violet » to « purple » because this term directly refers to a complementary currency used in the French town of Toulouse and is called « Sol Violette».

[ii] In the cryptocurrencies context, "mining" refers to the process by which computer calculation power is partly allocated to make virtual money transactions via computer easier and more secure. This service is paid for in virtual moneys.

[iii] REN stands for Reciprocal Exchanges Networks.

[iv] In this class context, a valorimeter can be viewed as a reference that assigns value to moneys.