Social Networking, 2017, 6, 164-180
http://www.scirp.org/journal/sn
ISSN Online: 2169-3323
ISSN Print: 2169-3285

Greek Political Language during the Economic Crisis—A Network Analytic Approach

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How to cite this paper: Kydros, D. and Anastasiadis, A. (2017) Greek Political Language during the Economic Crisis—A Network Analytic Approach. *Social Networking*, **6**, 164-180.
https://doi.org/10.4236/sn.2017.62010

Received: January 4, 2017
Accepted: April 25, 2017
Published: April 28, 2017

Abstract

In this paper, we seek to analyze pre-electoral political language in Greece with the use of Social Network Analysis. For this analysis, we collected data from the pre-elections speeches of five political leaders from the 20th of September 2015 Greek general elections. We proceed to form, analyze and compare networks of words with an emphasis on financial vocabulary. Findings can provide interesting insights into how political leaders structure their speeches, evaluate important issues and use economic terms and political rhetoric, while different structural patterns can reveal the differences between political parties. Finally, we check whether the overall networks follow the general rules of real-life networks by belonging to the small-world or scale-free categories.

Keywords

Social Network Analysis, Political Language, Greek Elections, Economic Crisis

1. Introduction and Literature

It is very well known that Greece has been in the middle of financial and socio-political crisis. The country's political life is characterized by the decline of traditional political formations, the emergence of new political forces, the formation of short-lived coalition governments and frequent elections. During a rather small time-window (2009-2015), five general elections were held in Greece, with seven different prime ministers. At the same time, financial terms and words are used increasingly in public political discourse and everyday discussions among citizens. Therefore, it is interesting to study how political leaders structure their speeches to address the pressing issues of this crucial and turbulent period.

The volume of social network research in political science has expanded radically in the last three decades, although this growth is characterized by conceptual disorder, heterogeneity and incoherence [1]. In [2], one can see a study of inter-organizational relations in the health and energy domains and [3] edited volume exposes network analysis to the wider audience. Recent research has focused on three types of networks [4]: government networks, which are formations of collaboration of governments; policy networks, in which actors negotiate and interact during policymaking processes; collective action networks, which depict different instances of collective action. Reference [5] presented a comprehensive overview of the research on policy networks, while [6] about collective action networks. In his empirical study, [7] examined 1014 publications related to political networks and identified their most common areas of inquiry: Europeanisation; governance/public policy; local, urban, and rural studies; non-governmental organizations and social movements; international relations; electoral systems and voting. Reference [8] has presented a concise review on the applications of SNA in political science.

Fewer scholars have tried to analyze political discourses using network concepts. However, there has been the significant increase in the relevant articles recently. Discourse network analysis has been utilized in various policy sectors: climate governance [9] [10], deforestation [11], nuclear power policy [12], pension politics [13], transport mobility [14], property rights [15], and shooting rampages [16]. These scholars combined content analysis and network analysis to analyze discourse networks, in which actors (parties, legislators, interest groups, and organizations) are connected to the concepts they employ [17].

Finally, network-based procedures have also been extensively applied in text analysis. Semantic network analysis [18] and network text analysis [19] [20] [21] are general labels which describe several relational approaches that seek to extract and represent networks from linguistic data. Reference [22] reviewed seventeen such approaches for constructing networks of words. In word-based networks the relationship between two words is determined by their proximity or co-occurrence within a given text range (e.g. a sentence; a window, n-words wide), whereas concept-based networks consist of connected concepts [23]. Relations can also be determined by the syntactic [18] or morphological and etymological structure of words [20]. Compared to traditional content analysis, network analysis focuses not just on frequency counts of concepts and words, but also examines their positional properties in order to highlight a text's key themes [21] [24]. Representing linguistic structures as networks allows connections within and between texts to be visualized in a simplified manner enabling researchers to identify otherwise invisible complex relationships [19].

In this paper, we use SNA methods to help the analysis of political discourse in Greece. We continue a previous similar work [25], which dealt with the January 2015 Greek elections. Here we deal with the pre-electoral period of September 2015. In both works, we construct networks of adjacent words using data from the pre-elections speeches of five political leaders. Words are organized into groups and are ranked according to their positions in the network. Furthermore, we explore whether the overall networks follow the general rules of real-life networks in the topological sense, by checking whether they exhibit small-world or scale free properties [26] [27]. Finally, we try to find out the differences between those networks and to examine how their different structures reflect the diverse political and economic views of the leaders. We also make some comparisons with January 2015 elections.

This analysis could be useful for political analysts and researchers to gain insight into political speeches. It could also contribute to network literature, as it explores the power of network models and rules in a new setting, Greek political discourse or political discourse in general.

2. Network Formation, Topology and Classification

In order to form our networks we use words as nodes and their adjacency within the text to be the connecting relation. This idea has been presented in [28], who used word adjacent networks to represent summaries of Portuguese texts as networks. Such a network can be considered either as directed or undirected, according to the decision whether the ordering of words should be considered.

Texts of words can be retrieved in many ways. We collected and concatenated all political speeches of leaders from the official webpages of five political parties, right after the 20th of September 2015 elections. These leaders were MrTsipras from SYRIZA (a radical left party at least at that time-period), MrMeimarakis from New Democracy (a center-right party), MrKoutsoumbas from KKE (the Greek Communist party, one of the very few left in Europe or even in the whole world), MrKammenos from Independent Greeks (a rather right-wing, anti-memorandum party) and MrsGennimata from PASOK (a socialist party which was changing places in the government of Greece for decades together with New Democracy). These parties represent very well the political spectrum in Greece. It was impossible to create networks from the other political party represented in the parliament (POTAMI), since they used a completely different approach during their pre-electoral fight, using mainly short social-media appearances or free interviews. Finally, we deliberately excluded the far-right, allegedly fascist, party of Golden Dawn. For this party and other similar movements in Europe, a different research work is currently been prepared, dealing again with word adjacency networks.

However, there exist a number of issues that impose a certain unnecessary complexity or even ambiguity in such networks. One such issue is common to all natural languages and has to do with different forms of the same word, for example in single or plural form. In languages with more complex grammar and/or syntax, especially in ones that have evolved over many centuries like the Greek language, even more problems exist because of different forms of adjectives and verbs or genders of words, or even many synonyms or ancient instances of the same word.

In [25], a pre-processing procedure has been introduced and we follow the same procedure for our September 2015 pre-electoral period texts. This procedure is mainly manual, since no proper automated tool was found. In short, adjectives, nouns and verbs were converted, pronouns were replaced by names, participles were treated as verbs or adjectives dependently, articles and other small words were mostly deleted but words like "we" and "you" were kept in place. In Figure 1, this procedure is shown in a short text, together with the created network.

After all necessary preparation procedures, simple ASCII texts were produced. We then used a small C language program to create edge lists and imported them to NodeXL, a semi-free Excel Template provided by the Social Media Research Foundation, in order to produce pictorial visualizations, to calculate centrality metrics and to investigate the community structure of our networks.

A sample view of one of the networks is shown in Figure 2, where MrTsipras' word-adjacency network is drawn.

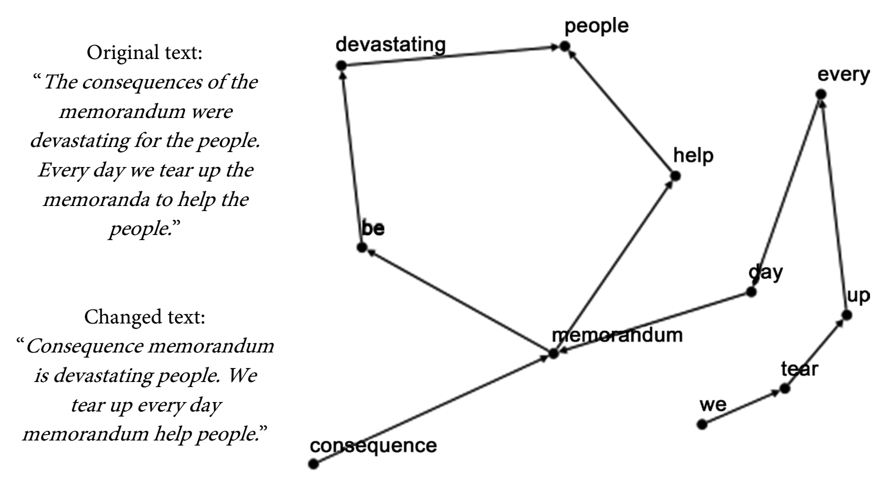

Figure 1. A sample text and its respective directed network.

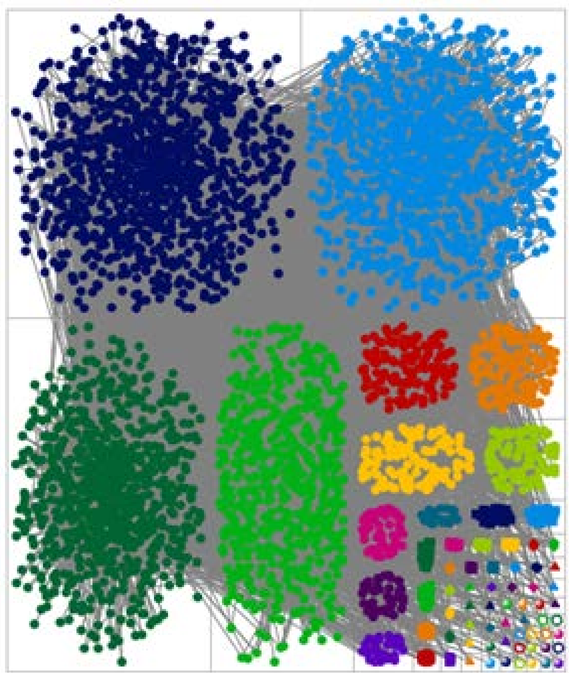

Figure 2. Mr Tsipras' word-adjacency network.

In Figure 2, we used NodeXL's feature to group communities of nodes (see Section 3) in the same area. Since all networks were created in similar manner, we choose not to represent all of them in this paper. Visualizations can give important insights to structure but not in large or similar networks.

According to [29], density, average degree, average distance, diameter and average clustering coefficient are a set of metrics that represent to a very good extend the topology of a simple, undirected network. In Table 1, we include all these metrics for our five networks.

A quite obvious difference between the networks of Table 1 has to do with the absolute numbers of nodes and links, especially for Kammenos' and Gennimata's networks. This difference has to do with fewer speeches uploaded in the parties' webpages, which in turn probably has to do with some lack of organization in these institutions, or because those parties considered enough to upload visual footage without any texts. It should be noted that MrKammenos' party is more of a coalition between smaller movements in the right spectrum and less a well-established political party. On the other hand, MrsGennimata's party (PASOK) has been a quite historical party but it came very close to become extinguished after a general (although not proven) popular belief that this exact history was one of the main factors led to the current crisis. The internal organization of this party (and of the New Democracy party too) has also suffered from poor financial management and extremely high debts to banks, loss of personnel etc.

MrKammenos' network has another interesting feature that makes a difference from the other networks, which is the increased density. Since density means that there exist more links between fewer nodes, this might mean a rather poorer vocabulary for the speaker.

Diversities are also the larger diameter and smaller average degree in MrsGennimata's network, probably induced through a rather loose use of language for this political leader or perhaps because of more different main ideas in her speeches.

According to [27], small average distance, small diameter and small values in average clustering coefficient, generally mean that the inspected networks are small-worlds. Furthermore, [26] have proven that in small-worlds the degree

Table 1. Basic topological features.

Metric	Political Leader's Network				
	Tsipras	Meimarakis	Koutsoumbas	Kammenos	Gennimata
Number of Nodes	3892	3071	3136	1704	1997
Number of Links	13,602	11,461	9756	4739	4064
Density (Undirected)	0.0024	0.0033	0.0026	0.0040	0.0029
Average Degree	9.27	10.15	8.30	6.97	5.8
Average Distance	3.33	3.10	3.41	3.31	3.78
Diameter	9	9	10	9	12
Average Clustering Coefficient	0.16	0.23	0.16	0.18	0.11

distribution follows a power-law curve. This property reflects the fact that in many real-life small-world networks there exist very few nodes with very high degrees, which also serve as hubs in the network, many more nodes with smaller degrees with an exponential tail. In our case, hubs serve as main ideas or words with very high emotional or economic impact and all other words have smaller importance and serve as background for the hubs. If one removes a node at random then probably nothing should happen to the robustness of the whole speech, since many nodes have small degrees. On the other hand, if a small number of hubs were deleted then speeches would collapse in small chunks of nodes.

It is not hard to check whether a network is a scale-free network by trying to fit its degree distribution to power law. We used the R statistical package [30] for all five networks and show our combined results in **Figure 3**, in log-log plots.

In **Figure 3**, we also show the computed alpha coefficient which in all cases is between two and three. From **Figure 3** and the accompanying computations, it is straightforward to see that all networks are scale-free ones. As already implied it is now obvious that when a political leader (or his/her speech-writer) prepares a speech, he usually uses a small number of main words and builds the rest of his speech around these main words-ideas. This should be done in every speech within the same pre-electoral period, or else the general ideas will not be distributed evenly to the population. If we want to find out which are these main ideas we can rank all nodes according to their degree centrality (see Section 4).

Small-world, scale-free networks are common in real-life networks. Recently it

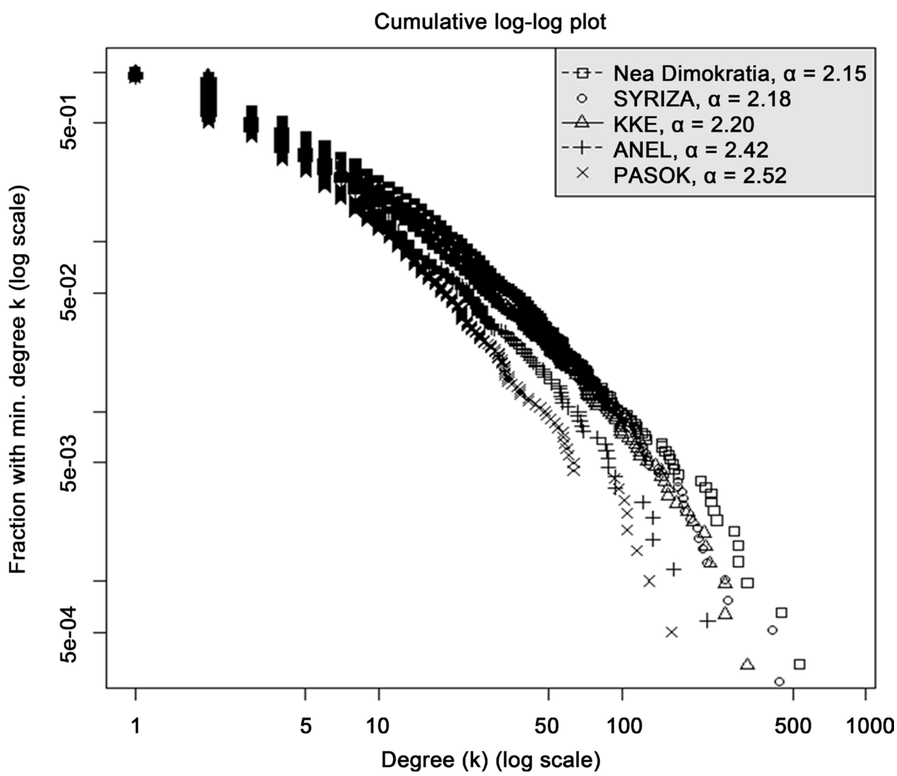

Figure 3. Fitting the power-law.

has been proven that they exist also in discourse networks. Both [31] and [32] found that epic works like *The Iliad* are scale-free networks with respect to the actor's interactions. The same results come from [33] regarding modern literature. The scale-free property is valid in various levels, from interactions of actors to interactions of words within the text. However it is very well expected that other types of discourse, like poetry, cannot hold such a property.

3. Community Structures

In Social Network Analysis, different groupings of nodes have been extensively introduced and used over the last decades. These grouping usually follow quite strict rules, thus resulting in rather hard to calculate, sometimes overlapping, groupings (see [34] for a full presentation). Recently [35] introduced the idea of communities of nodes. The main idea is that a group of nodes belong to the same community if more links exist between them than with other nodes, outside of this community. Reference [36] introduced a number of proposed algorithms to calculate communities. Furthermore, the metric of modularity has been introduced as a measurement that corresponds to the quality of grouping. If modularity is high then nodes tend to group in clearly bounded communities.

We used NodeXL's feature to calculate the community structures of all our networks and present our results and the relevant discussion in this Section.

In **Table 2** we show the most important communities in MrTsipras' network, which bears a modularity of 0.24. We also list the most central words with respect to PageRank algorithm within each community.

Community 1 mainly deals with the proposed political program and plan of SYRIZA and contains many economic words like development, economy, farmer, work, negotiation, product, production, business, worker, unemployed, tax, market, investment, liquidity. Community 2 refers to the contrast between SYRIZA (node we) and its political opponents. Community 3 reflects an opening to the Greek people and society who are called to support SYRIZA in the elections. Community 4 focuses on some important problems faced by the country (crisis, austerity, tax evasion, and refugees). Furthermore, there exist (but not included in **Table 2**) some smaller but distinct groups of 73 up to 116 nodes. Community 5 contains certain SYRIZA government's legislative interventions to rehire employees and protect primary residence, Community 6 deals with local

Table 2. Communities and most important nodes in Mr Tsipras' network.

Community/ Number of Nodes	Central Nodes with Respect to Page Rank
1/955	Political, new, public, program, social, plan, work, system, interest …
2/860	We, opponent, ND, old, interweaving of interests, debt, agreement, establishment, lender, corruption, authority, bank …
3/756	Whole, to have, the people, SYRIZA, no, you, I, Greece, citizen, Greek, battle, I can …
4/534	To be, great, country, other, crisis, many, problem, austerity, to confront …

issues, while Community 7 with the migrant issue. In the ranking, node we is by far the most important in the network.

Table 3 shows the most important (central) nodes within the four larger communities for MrMeimarakis' speeches. The network's modularity is computed to be 0.21.

In Community 1 the political and economic program of New Democracy is developed with positive words, while in Community 2 the speaker's personal tone is evident and his main objective is to denounce the policy of the SYRIZA-ANEL government (in Meimarakis and Kammenos networks the pronoun I is in the top five in the ranking of words, higher than in the other networks). In Community 3 the speaker addresses to Greek citizens and voters and urges them to choose a government of New Democracy rather than SYRIZA. In Community 4 node, we are dominant and MrMeimarakis speaks sometimes as a representative of his party and sometimes like an exponent of the Greek people to feature collective actions and collective emotions. As in Mr. Tsipras' network, there are a few smaller groups of 50-100 nodes each; Community 5 stands out for its structure, as it contains the references to amounts of money and financial resources. Regarding nodes' ranking, word we holds the first place, while Tsipras is especially high, at the third place.

In Table 4, we list the five larger Communities for MrKoutsoumbas' network together with some representative words. Modularity here is 0.25.

In Community 1, all the other parties and the new memorandum are the focus of intense criticism. In Community 2, which contains most of the financial words,

Table 3. Communities and most important nodes in MrMeimarakis' network.

Community/ Number of Nodes	Central Nodes with Respect to Page Rank
1/776	To be, new, to have, political, to exist, great, other, national, no, social …
2/639	Tsipras, I, opponent, woman, child, still/besides, to put, to create, world/people, human …
3/628	Whole, citizen, country, ND, you, Greece, government, to want, SYRIZA, to tell, must …
4/442	We, much, danger, start/principle, to cause, Thessaloniki, to pass, serious, fight, hope …

Table 4. Communities and most important nodes in MrKoutsoumbas' network.

Community/ Number of Nodes	Central Nodes with Respect to Page Rank
1/701	New, SYRIZA, government, memorandum, Popular Unity …
2/608	To be, the people, to have, I can, EU, popular, political, country, great, capitalistic …
3/603	We, opponent, KKE, party, Golden Dawn, system, you …
4/287	Whole, other, many, speech/reason, such, various, small …
5/131	War, indeed, migrant, region, small and medium, lie …

the alternative proposal of KKE for the economy is developed in response to the world of capitalism, monopolies and EU. In Community 3 voters are called to choose KKE as the only solution and not to support rival parties, especially Golden Dawn. Community 5 mainly deals with the issue of wars in the Middle East and the migrant wave. Finally, Community 4 appears balanced in economic, political and local references. The most important node here is the verb to be, followed by the people in second place.

Table 5 shows MrKammenos' network from party ANEL. This political party stands to the right of the political spectrum. However, it formed a coalition in government after the January and September 2015 elections. The modularity index here is 0.28.

Communities 1 and 3 have a strong political character: in Community 1 collective actions, decisions and attitudes of ANEL during coalition government are presented and explained, while in Community 3 the personal element dominates, as the leader addresses to his audience in first person and presents personal thoughts and actions. In Community 2 economic issues are mainly raised, such as the taxation of farmers, the return of deposits from abroad and the financial scandals of opponents, while Community 5 regards tax issues. In Community 4 the focus is on the country, the motherland and Greece's agreement with creditors, while Community 6 deals with the geopolitical position of Greece and the tourism issue. Finally, the preponderant node in the ranking is we.

In Table 6 we list the five larger Communities together with some representative words for MrsGennimata's network. Modularity was computed to be 0.31.

Community 1 is characterized by the attack against SYRIZA and ND, particu-

Table 5. Communities and most important nodes in MrKammenos' network.

Community/ Number of Nodes	Central Nodes with Respect to Page Rank
1/326	We, political, Greek, to do, the people, to give, first …
2/288	Not, farmer, euro (numbers), money, to go, to enter, PASOK …
3/279	To be, I, I can, to tell, you, ANEL, Greek, government …
4/256	Whole, country, other, to take, nobody, must, agreement …
5/141	Opponent, to have, business, to pay, person, interest, VAT, ENFIA, tax …
6/104	Greece, Europe, Hellenism, tourist, relation, Middle East …

Table 6. Communities and most important nodes in MrsGenimata' network.

Community/ Number of Nodes	Central Nodes with Respect to Page Rank
1/393	To be, Tsipras, SYRIZA, ND, I, government, to do, election …
2/365	New, great, Greek, social, every, public, system …
3/314	We, PASOK, whole, country, citizen, political, Greece …
4/133	You, member, space, democratic, cooperation …
5/126	Without, role, strategic, respect, potential …

larly for their attitude towards memorandum, while in Community 2 PASOK's program and proposals for the economy and the state are developed. Community 3 is dedicated to PASOK party and its relationship with the country and citizens. In Community 4 the speaker addresses to the audience on issues concerning them and at the same time she issues a call for concurrence to the center-leftists. Community 5 includes a series of rhetorical questions that invite people to ponder how Greece would be without the work of PASOK and a series of properties that should (like respect, trust, justice) or should not (corruption, exclusion) characterize politics. The most important word here is computed to be *we*.

4. Central Nodes Regarding Economy

Nodes are important in a variety of ways through special metrics. In this paper, five of these metrics were computed, namely: degree, closeness, between ness and eigenvector centralities, together with PageRank metric. The actual formal definitions of the above metrics can be found in [34].

Network metrics can facilitate qualitative analysis and comparisons over time and between parties. For this purpose, in **Table 7** we rank the fifteen most important nodes (after PageRank) regarding economic issues. For example, word agreement is the first word in this context for MrTsipras' network among all the network's words. We also include **Table 8** which shows the analogous ranking for the January 2015 elections, calculated in the same manner as in September's elections. In **Table 8**, MrSamaras' network represents New Democracy, sinceMr Samaras was the leader of this party (and prime minister in the previous period).

Table 7. Ranking of words about economy (September 2015 elections).

Rank	Tsipras	Meimarakis	Koutsoumbas	Kammenos	Genimata
1	agreement	farmer	memorandum	farmer	farmer
2	debt/duty	development	worker	agreement	development
3	creditor	economy	capitalistic	money	memorandum
4	development	memorandum	farmer	debt/duty	business
5	farmer	business	development	memoran-dum	investment
6	economy	bank	capital	list	production
7	agricultural	tax	unemployed	business	productive
8	work	resource	increase	pay	economy
9	product	investment	working	development	agricultural
10	business	job	job	bank	product
11	economic	economic	production	tourist	reduction
12	worker	unemployment	profit	market	resource
13	productive	capital control	capitalist	cruise	employment
14	production	NSRF	economy	expense	market
15	bank	reduction	pay	tourism	touristic

Table 8. Ranking of words about economy (January 2015 elections).

Rank	Tsipras	Samaras	Koutsoumbas	Kammenos
1	memorandum	development	worker	business
2	debt/duty	investment	working	debt/duty
3	austerity	debt/duty	unemployed	tourist
4	prog. Thess.	tax	capital	taxation
5	development	business	monopoly	farmer
6	troika	pay	job	pay
7	economy	reform	debt/duty	bank
8	bank	economy	memorandum	tax
9	agricultural	reduction	capitalistic	reduce
10	tax	money	salary	pensioner
11	economic	market	unemployment	creditor
12	farmer	reduce	development	pipeline
13	pension	money	pension	building
14	productive	deficit	economy	development
15	to tax	income	tax	fortune

PASOK was not represented in that study.

From Table 7 we can identify the economic issues in which the political leaders put more emphasis on the pre-election period of September. Words farmer and agreement (preferred by the coalition government) or memorandum (favored by the opposition) are at the top pentad in all networks. Word development is also prominent and is found within the ten first in all networks. Subsequently, words economy and business are common in four of the networks, while production and bank in three. Compared with the corresponding Table 8 for the January elections, in which debt was the dominant word, there has been a shift of focus of the speakers towards the issue of Greece's third bailout agreement and the measures it includes, especially for farmers. Word debt still remains in a high position in Tsipras' and Kammenos' networks (side of the coalition), while it has subsided to lower positions in opposition networks. Also, words tax and pension, which stood out in January ranking, are now lower (pension is even absent from Table 7). On the contrary, words development, economy and bank remain important issues in both elections.

The network structure and the way the words and therefore their concepts interact with each other can reveal the main political and economic positions of the party leaders, the differences between them, as well as possible changes and shifts in comparison with January elections. Thus, in Tsipras' network it is observed that:

- Compared with past election's top ranking, words memorandum, pension, program of Thessaloniki, to tax, troika and tax are missing now; indeed, the last three have dropped to much lower positions in the overall ranking (1108, 1344 and 1858 respectively).

- At the first place, memorandum has now been superseded by agreement. However, unlike memorandum, which was associated with negative words, agreement forms dyads with a series of verbs that emphasize its positive aspects (prevent, reverse, allow, terminate, finish, achieve, deal with, secure, save). Simultaneously, agreement makes dyads with other words that acknowledge the difficult points of the agreement (burden, negative, difficulty, condition, obligation, effect) or underline the belief that political opponents could not have brought a better deal (opponent, ND, Meimarakis, best, worst).
- Word farmer has risen in the ranking from 12 to 5 and is directly connected with words expressing an intention of supporting farmers, particularly on the issue of taxation (such as protect, support, relief, facilitation, income, expense, taxation, over taxation, fair, countervailing).
- Word debt remains high and is linked to words that indicate the party's intentions of public debt adjustment (depreciation, reduce, restructuring, interest rate), the size and the consequences of the debt problem (onerous, vice, burden, commitment, troublesome, exorbitant, pit, loop), and the criticism that the opponents incurred debts and argued incorrectly that Greek debt was sustainable (opponent, ND, create, multiply, asseverate, sustainable). Furthermore, other linked words refer to the belief that the rich must pay their debts (rich, debtor, media owner), whereas the debts of those in difficulty should be settled (settle, natural person, discharge).

In September's elections New Democracy had a new leader and in comparison with the January list, it seems that the top fifteen economic vocabulary now appears at lower positions in the overall ranking (namely from positions 23 - 109 in January to 56 - 181 now), suggesting perhaps that MrMeimarakis preferred to give greater emphasis to the political context than Mr Samaras did. Additionally, words debt, pay, reform, money, income, deficit are missing from the current top list. In Meimarakis' network:

- Making a new entry, word farmer lies at the top and forms dyads with problem, taxation, tax, nontaxable, devastate, destruction, impinge, be unfair, subsidy (to highlight the problems that arise due to the required measures of the agreement), with Tsipras, cheat, recall (to criticize the attitude of the government) and with the word no (to stress that the new measures for farmers cannot be accepted).
- Unlike MrTsipras, MrMeimarakis selects the term memorandum and tries to emphasize the negative aspects of the new agreement (new, worse, painful, bind), to remind the audience of MrTsipras' earlier statements about the abolition of the memorandum (Tsipras, abolish, rip, tearing up, change, finish) and to associate his political opponents with the signing of the memorandum (opponent, vote, bring, apply, sign).
- The words bank and capital control are new entries and show an effort of highlighting the problems that have arisen due to the increased deposits

withdrawals and imposition of capital controls. Typical are the words connected with bank (opponent, close, closed, collapse, charge, cost, 25 billion, recapitalization, withdraw), and with capital control (to trouble, strangle, drive off, stop, business, unemployment, worse). Other linked words (purpose, establish, underestimate) concern speaker's criticism that MrTsipras did not establish a special purpose bank, as promised.

The ranking in Koutsoumbas' network displays great similarities with that of the January elections. Even the words of the January list that are missing now can be found a little lower, within the first twenty five. At the first place, worker has now been superseded by memorandum, which pairs with words that not only reveal the KKE party's views about those who are responsible for the memorandum (SYRIZA, Tsipras, ND, Meimarakis, EU, system, government, troika, boss) and the negative effects of the measures (guillotine, barbarian, cruel, sacrifice, anti-popular, virulent, bankrupt, loss, burden, onerous, fire, VAT), but also denote an attitude of fight (release, combat, end, oppose, conflict, fight). As in January, so now, it is evident in the top ranking the influence of Marxist theory on the structure of economy and the conflict between two worlds, the workers, the unemployed and the farmers against the domain of big capital. This contrast is reflected in the following words that form pairs with capitalist and capitalistic: exploitation, brutality, jungle, altar, burden, antipopular, imperialist, competition, crisis, monopoly, EU, system, power, banker, business, property, market, Golden Dawn, profit, profitability, submission, support, rupture, overthrow.

In Kammenos' network several changes are distinguished regarding the top ranks. The most prominent word is farmer; connected words deal with farmers' issues, such as their taxation, debt cancellation, income, expenses and registration. Word agreement is accompanied by words that justify the decision of ANEL party to support the agreement and refer to its positive and negative points (succeed, achieve, wrong, upside-down) and the issue of the application of English law. Word memorandum continues to be associated with political opponents in a negative way (decrepit, impoverish, professional, boast, slump). Word debt remains at high ranks and is directly linked to deletion, elongation, opponent, settle, borrower, farmer, repayment, odious, disgraceful, serve. Finally, as in January, tourism issues are emphasised with the simultaneous presence of tourist, tourism and cruise in Table 7 while the word list refers to speaker's allegations of financial irregularities (combined with Lagarde, Luxembourg, Siemens, Christoforakos).

Finally, in MrsGennimata's network the most important node is farmer; adjacent nodes refer to the financial burden of the measures of the agreement for the farmers and to their taxation, training and access to the health system. Node memorandum is associated with words that express criticism of SYRIZA and ND for their stance on the issue of the memorandum and describe PASOK's main target: exit from the crisis and disengagement from the memorandum through a national plan and a national renegotiation team.

5. Conclusions and further research

In this paper, we tried to analyze Greek political language with the use of SNA. We utilised data from the pre-elections speeches of five political leaders from the 20th of September 2015 general elections in order to form word-based networks. Then, we used network metrics to detect communities and the most prominent words and subjects for each leader, particularly on the topic of the economy. Finally, we showed that all these networks were small-world and scale-free ones.

This approach could be fruitful for those who are interested to explore how politicians assess significant issues and formulate their objectives and election strategy. The network structure and the relations between the words can underline the basic positions of the rival parties. Network metrics can be used to identify and rank the central nodes that represent the ideas in which the political leaders put more emphasis. The locality of the nodes might also expose additional unknown and implicit context. Communities can highlight broader ideas and pre-electoral tactics. Moreover, the different structural patterns can show graphically the differences among political parties. For example, communities and central nodes in MrKoutsoumbas' network are very different, reflecting the influence of the communist theory. Finally, checking for small-world and scale-free properties can discover if there are any vulnerabilities (hubs).

In the Greek case particularly, we inspected a focal shift of the main problem of the country from national debt to the new deal with the lenders and the packet of measurements included, especially for farmers. Furthermore, the government coalition uses a type of vocabulary that enhances positive aspects of the deal, while the opposition does exactly the opposite. Issues concerning growth, businesses, productivity and the banking system are located in high ranks in leaders' agendas. Finally, groupings are similar in the sense that all leaders mainly choose three main directions: the presentation of their programs, attacking their opponents and appealing to the people's sentiment for support.

We finish our paper with some proposals for future research. This approach can be exploited in the long term for making comparisons between the political parties and detecting possible changes in their views and positions. Indeed, in Section 4, we made a comparison with the January elections with interesting results. A future research may focus on the political vocabulary in order to investigate each party's position along the political spectrum; or on the negative vocabulary, to study the way in which politicians attack their opponents. Furthermore, a potential future study can: consider the number of links between two words; create and analyze directed networks; investigate for the existence of different motifs in the networks of the political leaders or how their structure may relate with successful strategies. Finally, it can contribute to the finding and development of an effective automated tool which would be able to reduce the time of pre-processing.

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