

Changes in the connection networks of MEPs

Marits Márton, Bernát Ádám

Budapesti Műszaki és Gazdaságtudományi Egyetem
Project Laboratory

2023

Introduction

By its plastic nature, human connections change over time, especially when outside effects take place. However, in the case of policy makers, such changes will sooner or later have consequences to our life (As we live in the EU.)

Motivation

Understanding the network of MEPs might give us a better understanding of the following:

Motivation

Understanding the network of MEPs might give us a better understanding of the following:

- How smaller networks inbetween MEPs look like, their size and their quantity.

Motivation

Understanding the network of MEPs might give us a better understanding of the following:

- How smaller networks inbetween MEPs look like, their size and their quantity.
- **Identifying key decision and policy makers.**

Motivation

Understanding the network of MEPs might give us a better understanding of the following:

- How smaller networks inbetween MEPs look like, their size and their quantity.
- **Identifying key decision and policy makers.**
- **How events and occurrences shape the form and topology of the network.**

Motivation

Understanding the network of MEPs might give us a better understanding of the following:

- How smaller networks inbetween MEPs look like, their size and their quantity.
- **Identifying key decision and policy makers.**
- **How events and occurrences shape the form and topology of the network.**

All of these are helpful in understanding the processes regarding proposals and how they evolve into enacted laws.

Our Topic(s)

Our Topic(s)

- Our main focus was on the effects of **COVID-19** and how it shaped the network of **MEPs**.

Our Topic(s)

- **Our main focus was on the effects of COVID-19 and how it shaped the network of MEPs.**
- A more recent topic of interest might be the Russian-Ukrainian conflict and how it altered connections within the European Parliament.

Our Topic(s)

- Our main focus was on the effects of **COVID-19** and how it shaped the network of **MEPs**.
- A more recent topic of interest might be the Russian-Ukrainian conflict and how it altered connections within the European Parliament.
- For now, we focused on gathering information on **the whole dataset at once**, and we will focus on the changes over time in future research

Our analysis

We acquired data regarding amendments, for each amendment we know which MEP proposed the amendment, what kind of document it is, etc..

Our analysis

We acquired data regarding amendments, for each amendment we know which MEP proposed the amendment, what kind of document it is, etc..

Basically, we got a bipartite graph with node groups:

- MEPs
- Documents

Our analysis

We acquired data regarding amendments, for each amendment we know which MEP proposed the amendment, what kind of document it is, etc..

Basically, we got a bipartite graph with node groups:

- MEPs
- Documents

Edges \iff MEP made amendment to document

Our analysis

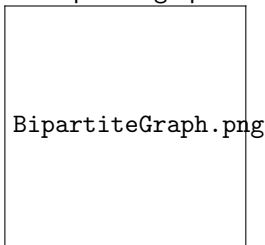
We acquired data regarding amendments, for each amendment we know which MEP proposed the amendment, what kind of document it is, etc..

Basically, we got a bipartite graph with node groups:

- MEPs
- Documents

Edges \iff MEP made amendment to document

A bipartite graph:



Projection

We then created a projection of this bipartite graph:

Projection

We then created a projection of this bipartite graph:

- Nodes: the nodes of MEPs

Projection

We then created a projection of this bipartite graph:

- Nodes: the nodes of MEPs
- Edges: 2 MEPs are connected if they amended the same document

Projection

We then created a projection of this bipartite graph:

- Nodes: the nodes of MEPs
- Edges: 2 MEPs are connected if they amended the same document











We have also considered and implemented weighted projection. We used the so called: "Collaboration weighted projection" (where we reward secluded document matching and punish popular document matching)

Analysis of activity by country

We are interested in analyzing how many amendments were contributed by each country's MEPs.











Analysis of activity by country

We are interested in analyzing how many amendments were contributed by each country's MEPs.

Country	Contributions
 Germany	5539
 France	4242
 Spain	3853
 Italy	3550
 Poland	2531
.	.
.	.
 Lithuania	541
 Cyprus	502
 Latvia	426
 Estonia	423
 United Kingdom	268

Analysis of activity by country











We are interested in analyzing how many amendments were contributed by each country's MEPs.

Country	Contributions
 Germany	5539
 France	4242
 Spain	3853
 Italy	3550
 Poland	2531
.	.
.	.
 Lithuania	541
 Cyprus	502
 Latvia	426
 Estonia	423
 United Kingdom	268

As one would expect, largest countries on top, small countries on the bottom.

Analysis of activity by country

We are interested in analyzing how many amendments were contributed by each country's MEPs.











Country	Contributions
 Germany	5539
 France	4242
 Spain	3853
 Italy	3550
 Poland	2531
⋮	⋮
 Lithuania	541
 Cyprus	502
 Latvia	426
 Estonia	423
 United Kingdom	268

As one would expect, largest countries on top, small countries on the bottom.

The UK is an outlier because of Brexit, as one would expect.

Analysis of activity by country

We are interested in analyzing how many amendments were contributed by each country's MEPs.

Country	Contributions
 Germany	5539
 France	4242
 Spain	3853
 Italy	3550
 Poland	2531
⋮	⋮
 Lithuania	541
 Cyprus	502
 Latvia	426
 Estonia	423
 United Kingdom	268

As one would expect, largest countries on top, small countries on the bottom.











The UK is an outlier because of Brexit, as one would expect.
(They left the European Parliament in January 2020)

Analysis of activity by country

Okay, so what if we normalize for population?











Analysis of activity by country

Okay, so what if we normalize for population?

Country	Contributions per million people
 Malta	1181.76
 Luxembourg	965.30
 Cyprus	546.78
 Slovenia	360.67
 Estonia	317.61
⋮	⋮
 Germany	66.54
 Poland	66.54
 France	65.01
 Italy	60.32
 United Kingdom	4.00

Analysis of activity by country











Okay, so what if we normalize for population?

Country	Contributions per million people
 Malta	1181.76
 Luxembourg	965.30
 Cyprus	546.78
 Slovenia	360.67
 Estonia	317.61
⋮	⋮
 Germany	66.54
 Poland	66.54
 France	65.01
 Italy	60.32
 United Kingdom	4.00

Here we see the smaller countries dominate the scene

Analysis of activity by country











Okay, so what if we normalize for population?

Country	Contributions per million people
 Malta	1181.76
 Luxembourg	965.30
 Cyprus	546.78
 Slovenia	360.67
 Estonia	317.61
⋮	⋮
 Germany	66.54
 Poland	66.54
 France	65.01
 Italy	60.32
 United Kingdom	4.00

Here we see the smaller countries dominate the scene
This is because EP seats are not distributed according to population

Analysis of activity by country

Okay, so what if we normalize for population?

Country	Contributions per million people
 Malta	1181.76
 Luxembourg	965.30
 Cyprus	546.78
 Slovenia	360.67
 Estonia	317.61
⋮	⋮
 Germany	66.54
 Poland	66.54
 France	65.01
 Italy	60.32
 United Kingdom	4.00

Here we see the smaller countries dominate the scene

This is because EP seats are not distributed according to population











More seats are given to smaller countries to boost their influence in the EP

Analysis of activity by country

So we should normalize for number of MEPs











Analysis of activity by country

So we should normalize for number of MEPs

Country	Contributions per MEP
 Luxembourg	103.83
 Malta	102.33
 Slovenia	95.00
 Slovakia	92.38
 Cyprus	83.67
⋮	⋮
 Poland	49.63
 Lithuania	49.18
 Italy	48.63
 Czechia	48.57
 United Kingdom	3.67

Analysis of activity by country











So we should normalize for number of MEPs

Country	Contributions per MEP
 Luxembourg	103.83
 Malta	102.33
 Slovenia	95.00
 Slovakia	92.38
 Cyprus	83.67
⋮	⋮
 Poland	49.63
 Lithuania	49.18
 Italy	48.63
 Czechia	48.57
 United Kingdom	3.67

The smaller countries do more, even in this chart

Analysis of activity by country

So we should normalize for number of MEPs

Country	Contributions per MEP
 Luxembourg	103.83
 Malta	102.33
 Slovenia	95.00
 Slovakia	92.38
 Cyprus	83.67
⋮	⋮
 Poland	49.63
 Lithuania	49.18
 Italy	48.63
 Czechia	48.57
 United Kingdom	3.67

The smaller countries do more, even in this chart

So the **MEPs of smaller countries contribute more** on average

Analysis of activity by EP Group

Which EP Groups were the most active?

Analysis of activity by EP Group

Which EP Groups were the most active?

EP groups are coalitions of parties from different countries

Analysis of activity by EP Group

Which EP Groups were the most active?

EP groups are coalitions of parties from different countries

The current EP groups are the following:

Analysis of activity by EP Group

Which EP Groups were the most active?

EP groups are coalitions of parties from different countries

The current EP groups are the following:

EP Group	Ideology	MEPs (pre-Brexit)
European People's Party (EPP)	center-right, conservative	176 (182)
Socialists and Democrats (S&D)	social democrat, progressive	144 (154)
Renew Europe (RE)	liberal, pro-Europe	101 (108)
Greens-European Free Alliance (Greens/EFA)	green, regionalist, pro-Europe	73 (72)
European Conservatives and Reformists (ECR)	conservative	66 (62)
Identity and Democracy (ID)	nationalist, euroskeptic	62 (73)
European United Left/Nordic Green Left (GUE-NGL)	socialist, euroskeptic	37 (41)
Non-inscrits (NI)	various	46 (57)

Analysis of activity by EP Group

Which EP Groups were the most active?

EP groups are coalitions of parties from different countries

The current EP groups are the following:

EP Group	Ideology	MEPs (pre-Brexit)
European People's Party (EPP)	center-right, conservative	176 (182)
Socialists and Democrats (S&D)	social democrat, progressive	144 (154)
Renew Europe (RE)	liberal, pro-Europe	101 (108)
Greens-European Free Alliance (Greens/EFA)	green, regionalist, pro-Europe	73 (72)
European Conservatives and Reformists (ECR)	conservative	66 (62)
Identity and Democracy (ID)	nationalist, euroskeptic	62 (73)
European United Left/Nordic Green Left (GUE-NGL)	socialist, euroskeptic	37 (41)
Non-inscrits (NI)	various	46 (57)

“Non-inscrits” is a French term for “non-aligned”

Analysis of activity by EP Group

Which EP Groups were the most active?

Analysis of activity by EP Group

Which EP Groups were the most active?

We gathered the following data on activity by EP Group:

Analysis of activity by EP Group

Which EP Groups were the most active?

We gathered the following data on activity by EP Group:

EP Group	#MEPs	Contribs/MEP
RE	108	83.29
S&D	154	75.79
EPP	182	73.54
GUE/NGL	41	44.29
ECR	62	34.16
Greens/EFA	74	30.92
ID	73	28.63
NI	54	11.37

Analysis of activity by EP Group

Which EP Groups were the most active?

We gathered the following data on activity by EP Group:

EP Group	#MEPs	Contribs/MEP
RE	108	83.29
S&D	154	75.79
EPP	182	73.54
GUE/NGL	41	44.29
ECR	62	34.16
Greens/EFA	74	30.92
ID	73	28.63
NI	54	11.37

We see that MEPs from the **left-wing and liberal parties** contribute the most amendments.

Analysis of activity by EP Group

Which EP Groups were the most active?

We gathered the following data on activity by EP Group:

EP Group	#MEPs	Contribs/MEP
RE	108	83.29
S&D	154	75.79
EPP	182	73.54
GUE/NGL	41	44.29
ECR	62	34.16
Greens/EFA	74	30.92
ID	73	28.63
NI	54	11.37

We see that MEPs from the **left-wing and liberal parties** contribute the most amendments.

There is also a tendency for larger EP groups to contribute more.

Centrality of MEPs

Which MEPs are the most central?

Centrality of MEPs

Which MEPs are the most central?

We analyze the 'degree centrality' of each MEP in the social network graph

Centrality of MEPs

Which MEPs are the most central?

We analyze the 'degree centrality' of each MEP in the social network graph











How many different co-contributors does each MEP have?

Centrality of MEPs

Which MEPs are the most central?

We analyze the 'degree centrality' of each MEP in the social network graph

How many different co-contributors does each MEP have?











MEP	EP Group	Degree centrality
 Hilde Vautmans	RE	183
 Karen Melchior	RE	173
 Marc Angel	S&D	169
 Olivier Chastel	RE	167
 Łukasz Kohut	S&D	166
 Michal Šimečka	RE	160
 Michal Wiezik	EPP	152
 Ramona Strugariu	RE	151
 Petras Auštrevičius	RE	151
 Maria Walsh	EPP	146

Centrality of MEPs

Which MEPs are the most central?

We analyze the 'degree centrality' of each MEP in the social network graph

How many different co-contributors does each MEP have?

MEP	EP Group	Degree centrality
 Hilde Vautmans	RE	183
 Karen Melchior	RE	173
 Marc Angel	S&D	169
 Olivier Chastel	RE	167
 Łukasz Kohut	S&D	166
 Michal Šimečka	RE	160
 Michal Wiezik	EPP	152
 Ramona Strugariu	RE	151
 Petras Auštrevičius	RE	151
 Maria Walsh	EPP	146











The most central MEPs come from **smaller and mid-sized countries**

Centrality of MEPs

Which MEPs are the most central?

We analyze the 'degree centrality' of each MEP in the social network graph

How many different co-contributors does each MEP have?

MEP	EP Group	Degree centrality
 Hilde Vautmans	RE	183
 Karen Melchior	RE	173
 Marc Angel	S&D	169
 Olivier Chastel	RE	167
 Łukasz Kohut	S&D	166
 Michal Šimečka	RE	160
 Michal Wiezik	EPP	152
 Ramona Strugariu	RE	151
 Petras Auštrevičius	RE	151
 Maria Walsh	EPP	146

The most central MEPs come from **smaller and mid-sized countries**

They mostly come from the more left-wing EP Groups such as RE or S&D.

Centrality of MEPs

A different approach to the centrality measure

Centrality of MEPs











A different approach to the centrality measure

We analyze the 'eigenvector centrality' of each MEP in the social network graph

Centrality of MEPs

A different approach to the centrality measure










We analyze the 'eigenvector centrality' of each MEP in the social network graph

MEP	EP Group	Eigenvector centrality
 Hilde Vautmans	RE	0.1127
 Karen Melchior	RE	0.1058
 Michal Šimečka	EPP	0.1031
 Olivier Chastel	RE	0.0998
 Marc Angel	S&D	0.0947
 Ramona Strugariu	RE	0.0943
 Sophia in 't Veld	RE	0.0892
 Łukasz Kohut	S&D	0.0884
 Nicolae Ștefănuță	RE	0.0867
 Dragoș Pîslaru	RE	0.0867

Centrality of MEPs

A different approach to the centrality measure

We analyze the 'eigenvector centrality' of each MEP in the social network graph

MEP	EP Group	Eigenvector centrality
 Hilde Vautmans	RE	0.1127
 Karen Melchior	RE	0.1058
 Michal Šimečka	EPP	0.1031
 Olivier Chastel	RE	0.0998
 Marc Angel	S&D	0.0947
 Ramona Strugariu	RE	0.0943
 Sophia in 't Veld	RE	0.0892
 Łukasz Kohut	S&D	0.0884
 Nicolae Ștefănuță	RE	0.0867
 Dragoș Pîslaru	RE	0.0867

As we can see, we have very similar results to the degree centrality

Centrality of MEPs

The betweenness centrality approach

Centrality of MEPs











The betweenness centrality approach

We analyze the 'Betweenness centrality' of each MEP in the social network graph

Centrality of MEPs

The betweenness centrality approach











We analyze the 'Betweenness centrality' of each MEP in the social network graph

MEP	EP Group	Betweenness centrality
 Fabio Massimo Castaldo	NI	0.0131
 Maria Grapini	S&D	0.0128
 Petras Auštrevičius	RE	0.0128
 Charlie Weimers	ECR	0.0123
 Annalisa Tardino	ID	0.0117
 Maria da Graça Carvalho	EPP	0.0116
 Sophia in 't Veld	RE	0.0109
 Maria Noichl	S&D	0.0109
 Luisa Regimenti	ID	0.0107
 Sirpa Pietikäinen	EPP	0.0100

Centrality of MEPs

The betweenness centrality approach

We analyze the 'Betweenness centrality' of each MEP in the social network graph

MEP	EP Group	Betweenness centrality
 Fabio Massimo Castaldo	NI	0.0131
 Maria Grapini	S&D	0.0128
 Petras Auštrevičius	RE	0.0128
 Charlie Weimers	ECR	0.0123
 Annalisa Tardino	ID	0.0117
 Maria da Graça Carvalho	EPP	0.0116
 Sophia in 't Veld	RE	0.0109
 Maria Noichl	S&D	0.0109
 Luisa Regimenti	ID	0.0107
 Sirpa Pietikäinen	EPP	0.0100

These MEPs are different compared the eigenvector centrality list which was *mostly* the repetition of the Degree centrality list.

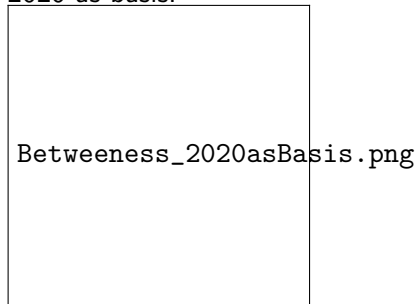
Behavior of central nodes

Betweenness centrality
2020 as basis:

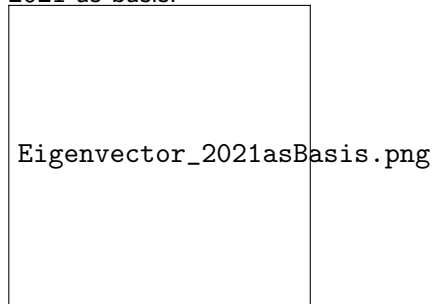
Betweenness_2020asBasis.png

Behavior of central nodes

Betweenness centrality
2020 as basis:



Eigenvector centrality
2021 as basis:

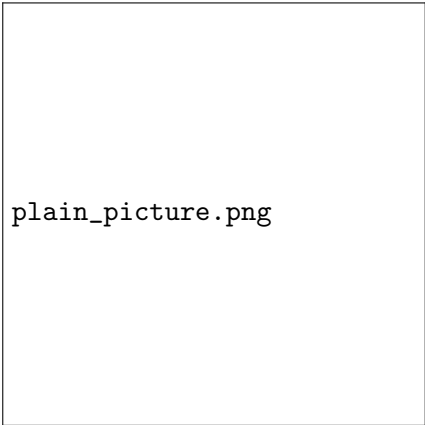


Projection

Some visualizations of the MEP social network graph (there were also some 0 degree nodes):

Projection

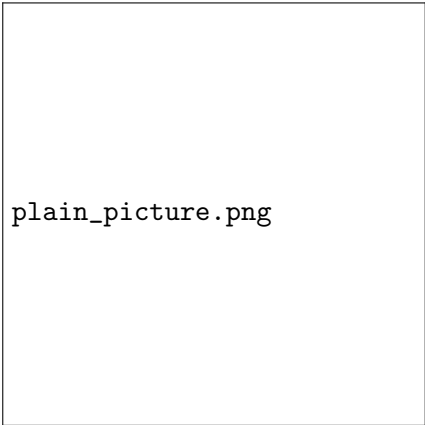
Some visualizations of the MEP social network graph (there were also some 0 degree nodes):



plain_picture.png

Projection

Some visualizations of the MEP social network graph (there were also some 0 degree nodes):



plain_picture.png

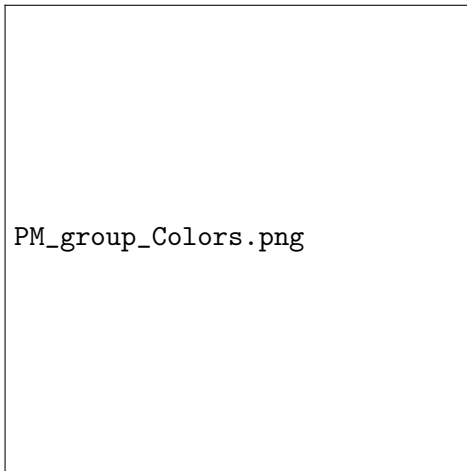
The Smaller interval ones look similar, however they aren't necessarily connected like this one

Projection

Color coding the nodes (according to EP groups):

Projection

Color coding the nodes (according to EP groups):



What's next?

We require additional data for multiple reasons:

- Cutting at more relevant dates, for finer distinction.

Further consideration might be fruitful, namely, the further useage of weighted projection. (Some machine learning opportunity)

Thank you for your attention!