Firms in the EU ETS: a categorisation based on transaction behaviour

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Context

The European Union Emission Trading Scheme (EU ETS):

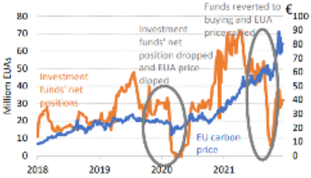
- Regulates the emissions of actors from the industrial, manufacturing and energy sectors. Also covers domestic aviation.

  ∼ *13000 regulated sites,*

  ∼ *40% of the EU's GHG emissions*
- Cap and trade system

EU ETS allowance price evolution

Context



Source: ICE, EEX, BloombergNEF. Note: Data is from Commitment of traders (CoT) database.

Investment funds' net position (2018-2021)[1]

Potential detrimental role played by purely financial actors
→ Report on the derivatives market activity (ESMA, 2022), EU discussions on banning financial actors

What are the different categories of actors in the EU ETS ?

- Summarise 2018 transaction behaviour based on network analysis
- Rely on clustering to deduct a categorisation of actors according to their transaction behaviour

Source: ERCST, BloombergNEF, the Wegener Center and Ecoact, 2022, Quemin and Pahle, 2021

Literature

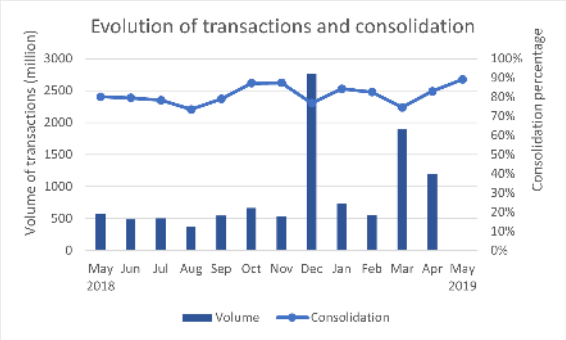
Empirical analysis exploiting transaction data	
Descriptive analysis	Trotignon and Delbosc, 2008, Martino and Trotignon, 2013, Ellerman and Trotignon, 2009, Lausen et al., 2022
Participation drivers	Zaklan, 2013, Jaraitė et al., 2013, Baudry et al., 2021 Hintermann and Ludwig, 2022, Abrell et al., 2021
Actor types	Betz and Schmidt, 2016, Balietti, 2016, Cludius and Betz, 2020
Market structure and properties	Borghesi and Flori, 2018, Flori et al., 2022, Karpf et al., 2018, Wang et al., 2020

Contribution:

1. mapping of the 2018 transaction network at the national firm level
2. categorisation of firms based on their network properties

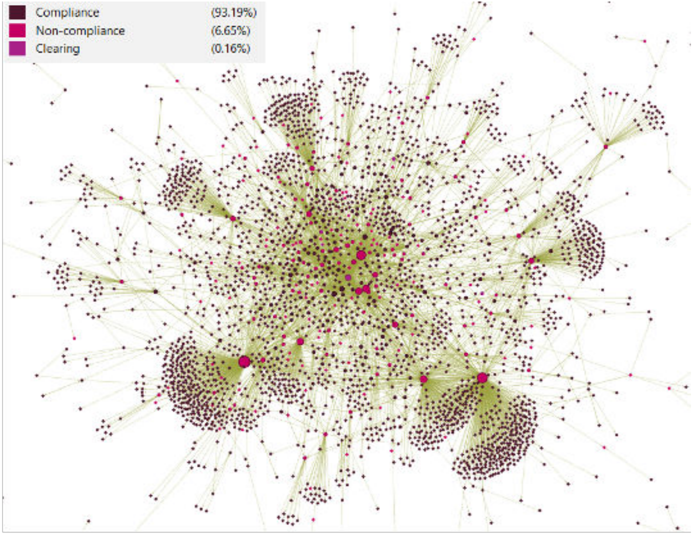
Data used

Data	***Information (Source)***
Transaction data	Account level data (EUTL database, Abrell, 2022)
Firm level ETS data	Match between the account holders and the companies (JRC, 2022)
Firm data	Ownership structure, NACE code (Bureau van Dijk ORBIS database)



Data transformation: administrative transfers removal, inter-firm and intra-firm transfer identification, auctions (Appendix).

The ETS network



Transaction network, 2018 (Betweenness centrality)

(Appendix: visualisation with other indicators, Auction network)

Methodology

K-means clustering (Hartigan-Wong algorithm, 1979)

$$Min \sum_{k=1}^{k} W(C_k) = \sum_{k=1}^{k} \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

W, the within cluster variation

C_k , cluster k

x, a data point belonging to cluster k

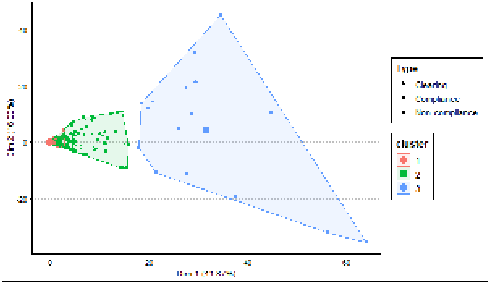
μ_k , mean value of the points assigned to the cluster k

Cluster variables:

- In/Out Degree
- Weighted In/Out Strength
- Centrality measures (Betweenness, Eigenvector, Harmonic closeness, PageRank) (Appendix)

(for transactions in auctions, in the secondary market and intra-firm transfers).

Firm clustering



Variable reduction using PCA:

- 58% of the variance is explained by the first two eigenvalues
- quality of representation and variable contribution (*Appendix*)

Cluster overview:

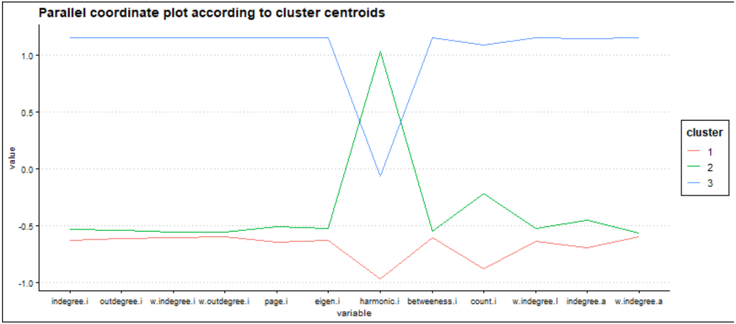
- 3 clusters of sizes 4378, 435 and 16
- Cluster 3: some financial and energy firms appear together
- Cluster 1: an important share of the regulated firms

Robustness: 2,3 and 4 clusters results, and divisive analysis clustering is also carried out. *(Appendix)*

Firm clustering

Cluster center characteristics:

- Cluster 3 stands out: upper tail of the distribution for all indicators
- Differences between cluster cluster 1 and cluster 2: harmonic closeness centrality, participation frequency in auctions and in intra-firm transaction.



(Appendix)

Conclusion/Next steps

Mapping of the 2018 EU ETS firm transaction network
→ revealed a fragmented network, and the intermediary role played by a handful of firms

Clustering based on network measures
→ Some financial actors appear to behave differently than others
→ Some energy companies have also been identified in this outlier category

Next steps:

- Explain the determinants of a firm belonging to a specific group - Latent profile analysis
  What explains the different transaction behaviour profiles in the EU ETS? (Appendix)

Thank you for your time and attention !

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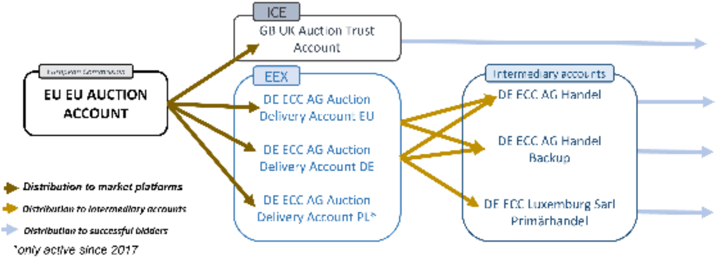
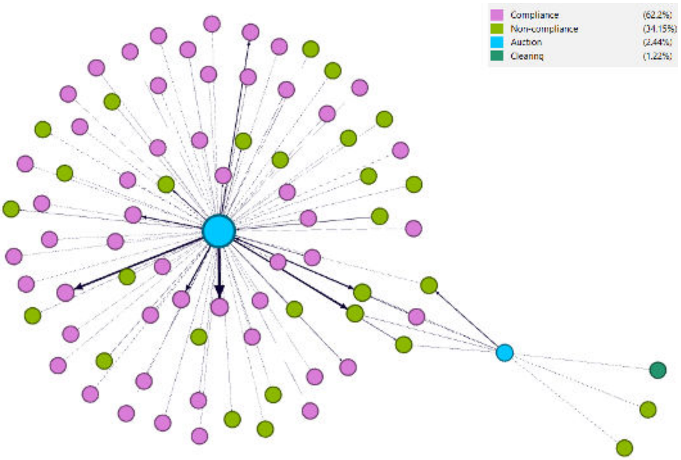
Appendix I



Auctioned allowances distribution

The details of the methodology can be found in the Climat & Débat, 2022 (p.13-14).

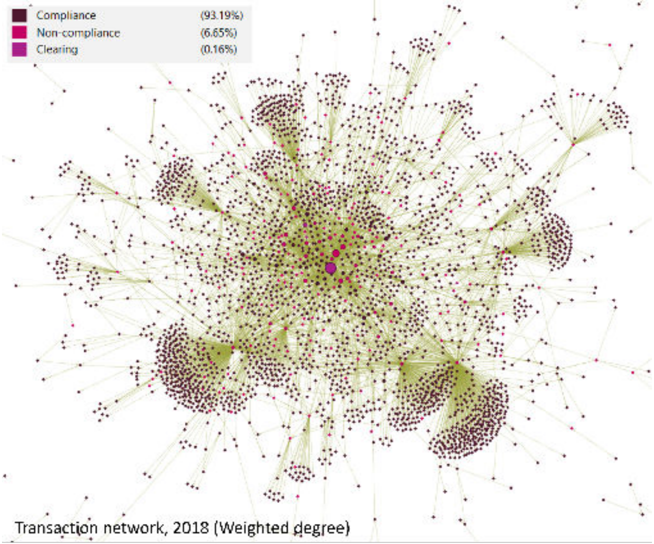
Appendix II



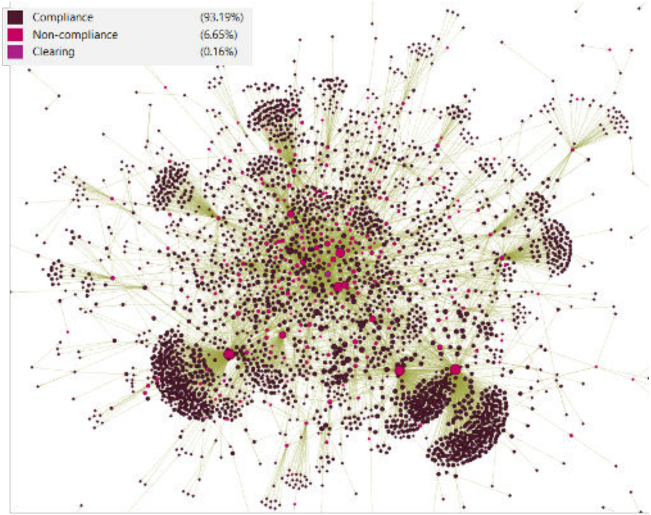
EU ETS firm auction transactions

The network is mapped by applying the Yifan Hu Proportional algorithm on Gephi.

Appendix II: weighted degree

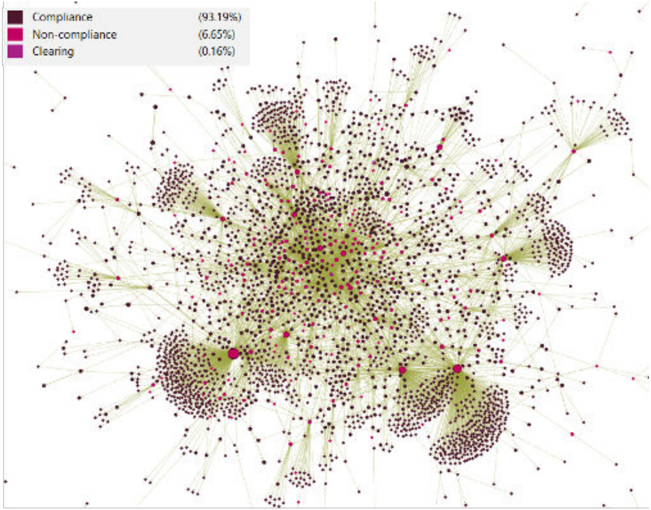


Appendix II: eigenvector centrality



Transaction network, 2018 (Eigenvector centrality)

Appendix II: pageRank



Transaction network, 2018 (PageRank)

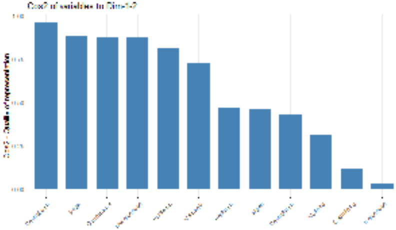
Appendix III: Network metrics

Indicator	*Definition*
In/Out Degree centrality	Local centrality measure indicating the connectedness of the firm. It counts the number of other firms that are directly connected to a firm, over the maximum degree that the firm can have: $C_{deg}(u) = \frac{d_u}{n-1}$, where d_u is the number of nodes that are connected to the node u and n is the total number of vertices in the network. As the transaction network is directed, In (purchase) and Out (sales) degree is distinguished.
Weighted In/Out Strength	This indicator computes the weighted degree of a node. $s_i^{in} = \sum_{j=1}^{N} w_{ji}$ and $s_i^{out} = \sum_{j=1}^{N} w_{ij}$
Betweenness centrality (Freeman 1979.)	Measures the centrality of a firm by looking at its role as an intermediator. The betweenness centrality of a node u is thus the number of shortest paths between a pair of nodes s and t on which one can find node u relative to the number of all shortest paths between s and t summed over all pairs of vertices. If $\sigma_{s,t}$ is the total number of paths between nodes s and t and $\sigma_{s,t}(u)$ is the number of paths between these two vertices passing through u, betweenness centrality is defined as: $C_{btw}(u) = \sum_{s,t \in V} \frac{\sigma_{s,t}(u)}{\sigma_{s,t}}$
Eigenvector centrality (Bonacich 1987)	On top of considering the number of links a firm has, this indicator also considers the centrality of the firm's neighbour. If A is the adjacency matrix of the network N where its elements $a_{i,j} \in 0, 1$ indicate the presence of a link (0 no link; 1 link) between two nodes i and j , and $M(i)$ is the set of neighbors of nodes i, the eigenvector centrality of a node is the sum of the centralities of its neighbors multiplied by a constant $\frac{1}{\lambda}$: $C_{eig}(j) = \frac{1}{\lambda} \sum_i a_{i,j} C_{eig}(j)$. Rearranged in matrix form one gets the eigenvector equation $Ax = \lambda x$ which is eponymous for this centrality measure.
Pagerank (Page et al 1999)	It can be interpreted as measuring the role of a firm in the network. The algorithm is similar to eigen vector centrality, but it only ranks nodes according to the structure of the incoming edges. The value of the PageRank can be defined recursively according to the formula: $PR(i) = \frac{1-d}{N} + d \sum_{j \mapsto i} \frac{PR(j)}{L(j)}$, where $PR(i)$ is the PageRank of a node i, N is the number of nodes, $L(j)$ is the total amount of links originating from j and the sum is taken over all nodes j having a link to node i. The quantity d ranges between 0 and 1 and represents the impact of a dumping factor, which is the probability that a given link can arise anywhere. As in the default case, here d is set to 0,85.

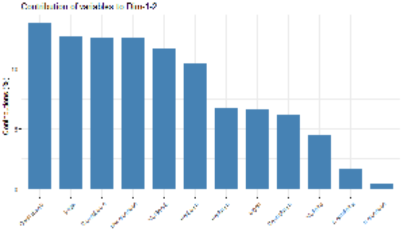
Statistic	Mean	St. Dev.	Min	Max
indegree.i	1.006	3.215	0	124
outdegree.i	1.006	8.988	0	405
w.indegree.i	1,004,407.000	16,176,495.000	0	893,693,002
w.outdegree.i	1,004,407.000	16,031,511.000	0	747,595,002
page.i	0.0002	0.0003	0.0001	0.013
eigen.i	0.031	0.061	0	1
btweenness.i	0.0001	0.001	0	0
count.l	2.832	12.687	0	395
w.indegree.l	396,777.600	5,172,144.000	0	167,542,724
indegree.a	0.017	0.137	0	2
w.indegree.b	173,320.800	3,353,682.000	0	145,830,000

Descriptive statistics of clustering variables

Appendix IV: PCA

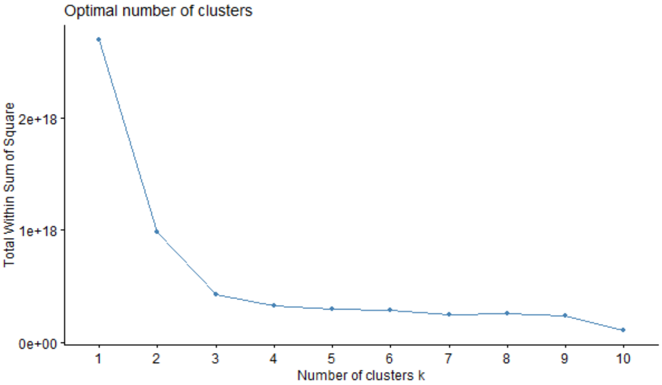


Quality of representation



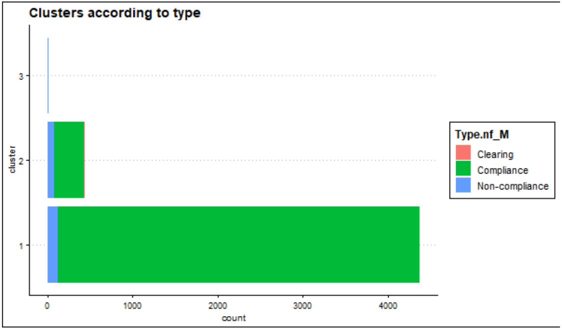
Variable contribution

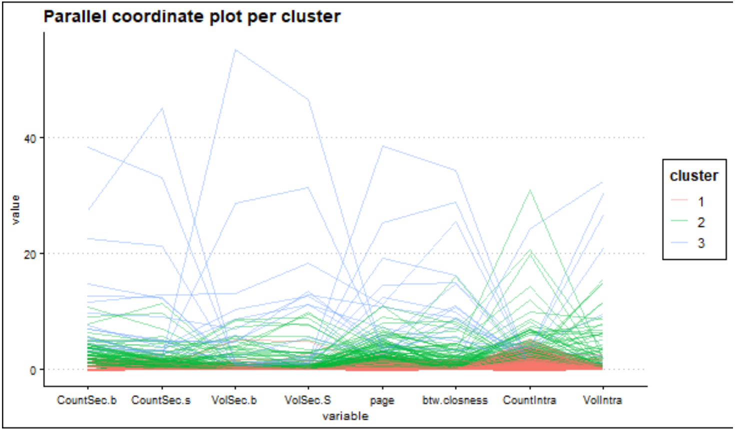
Appendix V: Kmeans Clustering



	indegree.i	outdegree.i	w.indegree.i	w.outdegree.i	pageranks.i	eigenc.i	harmonicc.i	betweenessc.i	count.l	w.indegree.l	indegree.a	w.indegree.a
1	-0.10	-0.08	-0.05	-0.06	-0.11	-0.07	-0.26	-0.08	-0.10	-0.07	-0.12	-0.05
2	0.55	0.37	0.20	0.18	0.70	0.42	2.57	0.35	0.89	0.41	0.95	0.15
3	11.47	11.01	8.96	10.68	10.37	7.97	1.01	12.82	2.83	7.67	8.09	9.98

Average of the cluster variables according to cluster


Clusters according to type
cluster
3
2
1
0
1000
2000
3000
4000
count
Type.nf_M
Clearing
Compliance
Non-compliance


Parallel coordinate plot per cluster
value
40
20
0
CountSec.b
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VolSec.b
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variable
cluster
1
2
3

Appendix : Latent profile analysis

What explains the different transaction behaviour profiles in the EU ETS?

LPA: statistical model to classify firms into mutually exclusive and exhaustive classes

- use the transaction behaviour variables for the creation of classes
- specify firm information data as covariates

Variable	Details
Sector	Energy, Carbon leakage, finance, other (NACE code)
Productivity	Revenue/number of employees
Compliance	(dummy, regulated or not)
Net balance	Free allocation - verified emissions
Net market size	Banked allowance estimation

List of covariates