A Longitudinal Network Analysis of the Space Sector Using International Trade Data

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Abstract. The space domain is attracting increasing commercial and military interest, and thus there is an interest from several parties to better understand the actors in this domain, and their interrelations and interdependencies. While there have been several methods proposed for studying separate state space actors, few attempts have been made at quantifying the intricacies of the interrelations between these actors. In this work, we propose a novel approach of modeling the interrelations between state actors in the space domain using social network analysis, based on global space trade data over a 20-year period from the International Trade Centre. We show how this data can be visualized and then utilized for longitudinal studies, demonstrating the dynamic evolution of the global space trade network over time. Although few comparable studies of the space domain have been performed, our results are in agreement with our previous research on space trends, using other quantitative and qualitative methods. Considering the increasingly "congested, contested and competitive" nature of the space domain, and the emergence of an increasingly multipolar space trade landscape, we find that the proposed method can constitute a valuable addition to any space domain analyst's toolbox.

Keywords: Space Actors, Space Domain, International Trade, Space Trade, Social Network Analysis, Graph, Time Series, Longitudinal Network Analysis.

1 Introduction

The past three years have seen record numbers of satellite carrying rocket launches. In addition to this, each individual launch today, on average, carry several multiples more satellites compared to 10 years ago and there are now around 8000 active satellites on orbit. What was once seen as mainly the domain of expensive national space programs is now dominated by commercial activity contributing to a majority of the active satellites [1]. The commercial actors contribute with rapid technical innovations and the proliferation of space systems, often using satellites that are smaller than their historic counterparts. In fact, space has never been more accessible for emerging nations with spacefaring ambitions. Research into the space domain therefore requires an increased understanding of the quick and dynamic developments and the interactions between the actors within it. Although recent years have seen some examples of published work, applying methods of social network analysis to the space domain have so far been underutilized in the research and exploration of the actors in space.

In this paper we present a novel approach for studying the dynamic evolution of the space domain using social network analysis and graph theory. By using international trade data within the space sector we show how decision makers can gain insight about space trade relations between state actors on the macro level and how the number of actors and the links between them have evolved over the past 20 years along with the shifts in communities and central actors that exist within the networks.

1.1 Background: The Evolution of the Space Domain

The space domain is currently undergoing a period of rapid change, with growth driven by both expanding commercial interests and technological advances [1]. In addition, the military interests in space are increasing as more nations adopt the view of space as a domain for military operations. At the same time, due to the inherent dual use nature of space systems (i.e. their application for both military and civilian purposes), the already blurred delineation between commercial and military utility of space systems is getting even blurrier. New spacefaring nations are emerging at an increasing pace, and the space economy is growing in terms of turnover, as well as the number of state and industrial actors involved. This has all resulted in a dramatic increase in the number of active satellites, which has more than quadrupled over the past five years, posing challenges for the coordination of space traffic and issues pertaining to space safety and security. Thus, the commonly used description of the space domain as increasingly "congested, contested and competitive"[2] rings ever more true.

2 Related Work

Previous research into the actors of the space domain has to a large extent focused on qualitative analyses in the study of space power in order to categorize either the capabilities and capacity of the actor or their international cooperation. A recent example of this is Aliberti et al[3] who develop a method to categorize 11 space state actor types based on 94 indicators from which two indices are defined. Similar approaches have also been applied to the characteristics of international cooperation in order to advise emerging space agencies [4] or quantifying specific aspects of an actors space power [5]. Finally, studies exploring the economic aspects of space can also be found. Clark et al[6], for example, review methods to evaluate the effects of public investments into the space sector and their resulting economic and social effects on society.

Only recently have studies appeared where social network analysis is applied to the space domain. Ben-Itzhak[7] studies international space agreements between states in order to map the formation and evolution of *space blocs* pre and post 2008. Another, comprehensive, study by Morin and Tepper[8] assesses states' structural power in the space domain using bilateral treaties concluded by states and their governmental agencies. Other types of space agreements have also been considered such as data sharing agreements within the *space situational awareness* (SSA) sector [9]. Other examples show network analysis aimed at studying space governance and organisational structures [10], space business sectors [11] and the uses of satellite imagery in agriculture [12]. These studies provide examples of the insights that can be gathered from performing network analysis on different types of international agreements. It is clear that social network analysis is an emerging method in the study of the space domain. However, international agreements tend to be static and may not be able to describe the rapid development of the space domain and as such we require new, dynamic, activity-based metrics to accurately map and characterize this evolution. We hope that this study demonstrates that trade data is one such metric which, combined with network analysis, provides policy and decision makers with an understanding of the developments in space over the last two decades.

3 Methodology

3.1 Dataset Characteristics

Annual import and export data, available through the International Trade Centre[13], and their Trade Map tool[14], consists of compiled data in US Dollar Thousands based mainly on values from UN Comtrade[15] as well as national sources. Trade data are categorized using the international standardized *Harmonized Commodity Description and Coding System* (HS) and in the case of this study we use data under code 880260 *Spacecraft, incl. Satellites and Suborbital and Spacecraft Launch Vehicles* to analyze state actors in the space domain. It is well known that differences can exist between the corresponding reported import and export values between partner countries [16]. This happens for a multitude of reasons such as local trade systems, quantity measurement, time lags in reporting, misallocations, confidentiality, re-exporting and differences in transportation and insurance costs. Trade values within HS Code 880260 exhibit large variations in the reported values over time and entries can be sparse for some countries. For example, space actors with a prominent presence throughout the space age (e.g. the United States of America) report significant trade values throughout the entire studied period (with the exception of 2010). On the contrary, smaller, or emerging, space actors only report values for occasional years. Lithuania, for instance, reports no values except in 2013, 2019, 2020 and then again in 2023. Nevertheless, it has been shown that using expanded trade networks, instead of focusing on bilateral trade flows, using all available trade data provide the foundation for robust analyses of centrality [17] and international trade data from other HS codes, in general, and specifically from ITC, have previously been used to perform network analyses (*cf.* [18, 19]).

Using data provided by ITC we construct a dataset of yearly values of import and export regarding space trade from 2001 to 2023 suitable for longitudinal network analyses characterizing the evolution of the space domain. As such, we use the import and export values to construct one large expanded directed network of space trade. It is worth mentioning that, although we believe HS code 880260 to be highly relevant for studying the space domain, there may also be other relevant HS codes pertaining to space data, subsystems or materials required for such activity. It has to be noted that a strength with this particular HS code is that it seems to be more or less globally adopted, whereas other codes (particularly subcodes of HS code 880260) are used only by a few countries.

3.2 Constructing Graphs of the Space Domain

Using the space trade dataset, we construct unimodal weighted directed graphs where individual countries comprise the nodes in our network and the trade between them define the edge weights that connect them. Projects pertaining to space systems are often long which can contribute to our dataset tending towards sparsity for some actors. In order to address this we choose to construct our graphs using a moving average. We empirically found that using a window of 3 years provides a good balance between smoothing out sparse data and still being dynamic enough to capture discernible trends.

Due to discrepancies existing between trading partners' self-reported trade values we risk duplicate edges existing in our edgelist. In the cases where this happens, we compare the values and choose the larger value as our final value to be represented in the edge list and compute the average trade over the time period relating to import and export. We automate this task using Python and construct our graph objects using the library *NetworkX*[20]. Even though the average trade value defines our foundational edge weight, we compute additional weights. These include the cumulative trade value and the logarithm as well as its inverse of both the cumulative and average trade value. We apply the same formulation as that used in the log-weighted and popular *ForceAtlas2* layout algorithm[21]:

$$W_{i,j} = \mathrm{Log}_{10}(x + 1) \tag{1}$$

where W is the weight connecting node i and j and x is the input weight, as any weighted values of 1 would otherwise render a weight of 0. This approach allows us to construct networks over various time spans throughout the possible range in our dataset.

To visualize closely associated nodes we apply a community detection algorithm and embed the results into our graph object. Several available methods to assess network communities exist and have been explored. This study uses the *Clauset-Newman-Moore* algorithm known as the *greedy modularity optimization algorithm*[22], which has successfully been applied to trade networks previously e.g. [23], and allows the incorporation of trade value for the optimization of community. Other algorithms, such as edge betweenness partitioning which would otherwise, incorrectly, partition by breaking the highest cost links in the network. We use the greedy modularity algorithm implemented within *NetworkX* and use the average trade over the time span as our edge weights along with a resolution of 1 for modularity optimization of the intra- and inter-connected edges with respect to the community in question. We allow for a lower limit of 4 and an upper limit of 20 communities to be resolved within our graphs.

3.3 Graph Layout

To determine the layouts of our space trade networks we choose to use a combination of two different layout algorithms. For the initial positions we first apply the *Kamada-Kawai* layout algorithm[24] to our graph object using the inverse logarithm of the average trade value as weight. This algorithm optimizes the node position based on a least cost path function. As *Kamada-Kawai* minimizes edge length between nodes choosing the inverse value as weight promotes countries with high trade between them to be more closely positioned as high trade values will now be small. Furthermore, as previously stated, the high variance in trade values occurring in the dataset justifies using the logarithm of trade as ensures a tighter layout. After this initial step we applied an open source version of the *ForceAtlas2*[21, 25] algorithm without considering the edge weights to regularize the visualization and create a clearer picture of clustering and separating any tightly grouped nodes. Finally, we remove isolated nodes, particularly those pertaining to non-specified trade entities and self-loops (see Fig. 1).

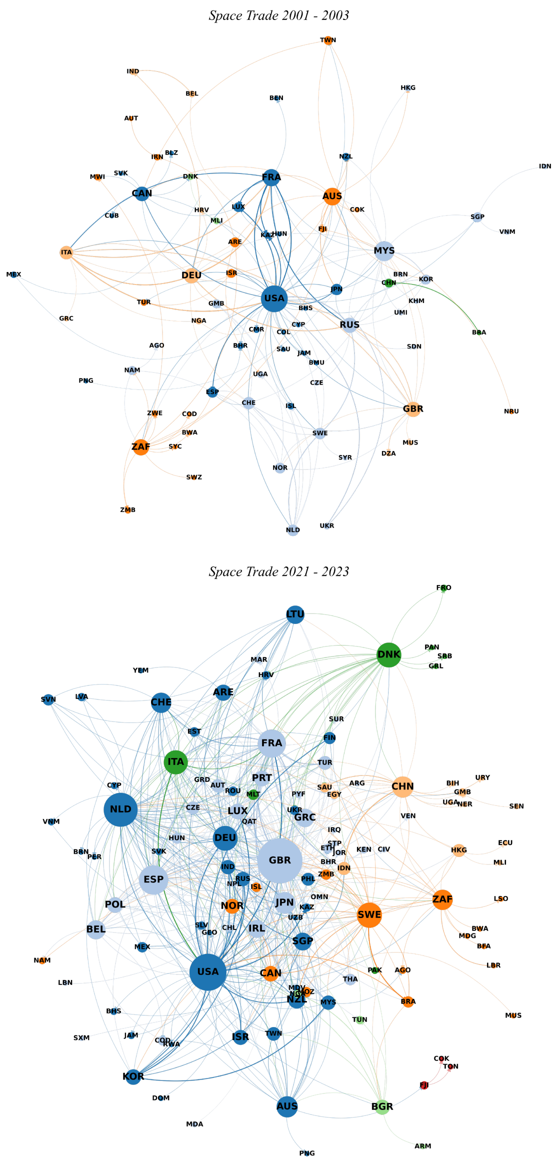

Fig. 1. Two time steps within our longitudinal graph time series generated using our workflow. (Above) The space trade network as it was in 2001-2003. (Below) The space trade network for 2021-2023. The node size visualizes the degree centrality and the edge thickness the trade value. The colour visualizes the community generated by the greedy modularity algorithm based on the average values of trade for the three-year time period. It is readily apparent that an increase in network size has occurred and that more actors are competing for central positions in the network.

3.4 Time Series Analysis and Centrality Measures

Using the established workflow, we can now apply it incrementally using a three-year moving average sliding window approach to create a time series list of graph objects, or a longitudinal network analysis. As our dataset ranges from 2001 to 2023, this workflow results in a time series including 21 time steps from 2002 to 2022. From this list, we can extract centrality measures or network properties. As we weight the network edges by the average 3-year trade value, centrality measures that focus on least-cost link analysis, such as betweenness, become less informative. Instead, we use the common degree centrality (Fig. 2A) to assess centrality based on an actor's number of trade connections. Furthermore, it has been showed by Sajedianfard (2021)[17] and other studies that eigenvector based centrality measures have been particularly useful for directed trade networks. The pagerank measure, using the average trade value as weight, assesses the centrality based on that of the actor itself and the actors with which they are connected (Fig. 2B). Finally, looking at inwardly directed and outwardly directed edges, also weighted by the average trade value, through the HITS algorithm allows assessing the characteristics of the trade flow in the network. The inwardly directed trade values can be assessed through the *authorities* value (Fig. 2C), and outwardly directed trade values through the *hub* measure (Fig. 2D)[26]. We calculate these measures for eight historically, and currently, prominent state actors in the space domain, The United Kingdom, The United States of America, France, The Russian Federation, India, Japan, Italy and China, for the graphs in our longitudinal time series. These actors feature in our networks and rank as central actors, however it can be argued that as the space domain develops there is an increased need to consider additional state actors. Finally, we present the evolution of our networks by the number of nodes and edges present in our graphs over time (Fig. 3).

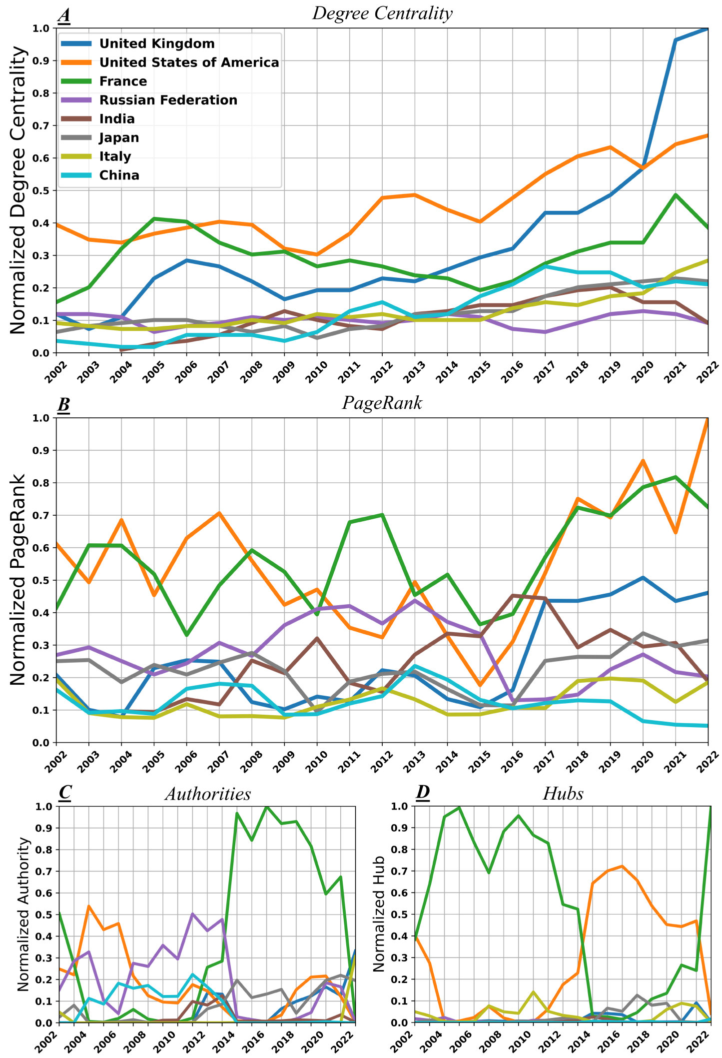

Fig. 2. Four centrality measures depicted for eight historically prominent space actors for the studied period. (A) The normalized degree centrality in which The United Kingdom can be seen to become a highly central actor as the actor with the most trade connections. (B) The pagerank centrality measure indicate the US and France to be highly central actors in space trade over time with the exception of 2014 and 2015 in which India and the Russian Federation also rank highly. 2017 onwards also sees the UK rank highly. (C) The authority measure shows important states with regards to inwardly directed connections and illustrate three phases. The American phase (2002-2008), the Russian phase (2008-2014) and the French phase (2014-2022). (D) Important states with outwardly directed connections can be measured using their hub values and is dominated by France and the US in two phases. The French phase (2002-2013) and the American phase between 2013-2021

4 Results

When viewing the global space trade network graphs in Fig. 1, some key characteristics can be demonstrated. The graphs provide a visual way of quickly determining the central and/or influential space trade actors from their number of connections indicated by node size, their location in the graph and the size of the trade value that connect them, indicated by the width of the edges that connect them. Looking at actors' relative locations in the graph indicates between which actors there are strong connections. Furthermore, the associated trading partners can be assessed by their communities (represented by node colour) and in the way the communities intermingle which provide indications about connections or similarity in some dimension between certain actors where such connections or similarity might otherwise not be obvious. When studying the space trade network's evolution over time, by contrasting the two graphs in Fig. 1, the characteristics mentioned above can be used to draw further conclusions. It can readily be seen that the network has evolved to become denser (see also Fig. 3), with both more actors and more central actors, and with more connections between actors in general. It can also be seen that several actors have changed communities, sometimes to such a degree that virtually entirely new communities emerge.

The degree centrality (i.e. number of trade connections) over time for the subset of 8 space actors (Fig. 2A) show, unlike the snapshot character of the graphs in Fig. 1, an easily digested illustration of the development over time of an important variable showing one aspect of an actor's influence in the space trade network. The most immediate observation is the pure ranking aspect, i.e. which lines are in general positioned above each other. Furthermore, fluctuations in the number of trade connections and possible correlations between trends for different actors can readily be identified. There is a general increase in the degree of the presented actors compared to 20 years prior. However the increase in degree for the UK, which ranks the highest in this regard, stands out. The pagerank measure (Fig. 2B) which includes the trade values in its assessments, demonstrates the US and France to be the highest ranking actors in the space trade over the course of the studied period, with the exception of 2014-2016. Russia ranks highly between 2009 and 2015, and from 2017 and onwards the UK assumes third place after the US and France. The measure of authority (Fig. 2C) demonstrates three phases in which different state actors have assumed a highly ranking role. The first characterized by the US ending in 2007, the second by Russia ending in 2014 and the final by France. However the end of this third phase shows a declining trend for France and it is unclear if this indicates that the space trade is entering into a new phase. The final measure of a state actors role as a hub (Fig. 2D) once again singles out the US and France to rank significantly higher than other actors. 2002 through 2014 shows France assuming the highest rank but declines by 2014 in which the US increases in this measures up until the final time step in which France yet again ranks highly.

Another way of displaying the development of the space trade network globally over time is by looking at the evolution of the number of nodes and edges. Fig. 3 provides a quick overview of how the number of actors, and the interconnectedness between them, in the space trade network varies over time. Besides providing a separate reading of the two variables, one can also look at the correlation, or lack thereof, between changes in the variables indicating how the density of the network changes. Indeed, this figure shows the increase in state actors and trade activity within the space sector with a rapid positive increase occurring starting in 2015 using our method of analysis.

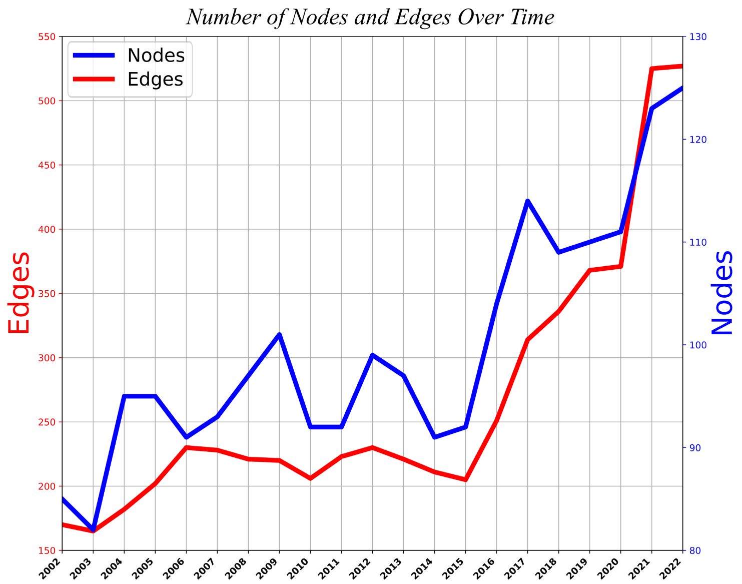

Fig. 3. The number of nodes (blue) and edges (red), in our longitudinal space trade graph. A rapid increase can be seen to occur starting in 2015.

5 Discussion

5.1 Limitations

The main limitation of this analysis stems from the characteristics of the dataset provided by ITC. It is well known that self-reported trade values differ in value, in choice of HS codes, or due to countries abstaining to report any value at all as discussed in 3.1 and Chen et al. 2022 [16]. For this reason, our dataset must be considered incomplete. However, even though data may be lacking for individual entries it has been shown that expanded trade networks, using the fully available data, still provides a robust measure of node centrality metrics [17]. Furthermore, this study relies on countries engaging into international trade and thus does not capture domestic trade. Indeed, many space programs have historically tended to be, and some still are, strictly domestic state interests. Relatively small international trade could thus instead be interpreted as the result of a determined strategy for strategic autonomy or as a result of imposed sanctions. For this reason, some larger space powers may appear as smaller actors in our graphs and vice versa.

5.2 Implications of our Network Analysis of the Space Trade

The strength of this analysis is that it provides a way to visualize the interconnectedness and relationships of state actors based on the reporting of others and so produce a large-scale overview of the entirety of the space trade domain.

It is clear that the space domain is growing from our graphs (see Fig. 1 and Fig. 3). However, even if the number of actors in general has increased and are increasingly interconnected compared to 20 years ago, there are still relatively few actors that dominate the network when examining the metrics that take trade value into account – in this study this comprises France and the United States (see Fig. 2B).

The United Kingdom's recently declared ambitions to become a major player in the international space sector [27] correlates with results of our analysis. It has become the state actor with the most connections (see Fig. 2A), positioning it in a highly central position in our visualization of the 2020 – 2023 network (Figure 1). The nation's role as a leading space actor is however yet to be demonstrated in the country's associated trade values but is on the rise as deemed by the pagerank metric, but will be a topic for further study in coming years. Furthermore, it can be seen that while the US and France dominate the space trade, the two actors assume alternating roles as authorities and hubs over the studied period (Fig. 2B,C,D). The exception to this is the high authority measure assumed by Russia during 2008 – 2014 which abruptly ends, likely due to sanctions imposed on the country after the annexation of Crimea. It is therefore not surprising that the pagerank measure show the time period surrounding 2014 to be a time of change before a new order is established.

The rapid growth in the number of nodes and edges starting in 2015 (Fig. 3) correlates with several trends observed in our recent report on global space trends [1], e.g. an accelerating increase in the number of spacefaring nations around this time. However, the rapid growth of the space trade network will be limited by the relatively finite amount of states that can partake in it. Furthermore, this growth is associated with an increased density of the network. This exemplifies the increasing activity and interconnectedness of commercial space but is also an effect of this finite growth possibility of the network. It is in accordance with observations from other network analyses of international trade that compare these to the theories of small world graphs with small degrees of separation [18].

In addition to this, we successfully identify communities in our networks using the *Greedy Modularity Algorithm*. It is clear that these in fact intertwine with one another, as exemplified mainly by the European and North American state actors. However, we argue that the communities provide valuable additional information in interpreting preferred trading partners. Interestingly, the network of 2021 to 2023 (Fig. 1), towards the right side, exhibit clearer signs of clustering (parts of the network dominated by individual nodes to which other smaller nodes connect). This development and the community compositions will be an important aspect to follow in the development of the space domain to understand the nature of space cooperation going forward and the trend toward an increasingly multipolar space domain.

5.3 Graphing the Dynamics of the Space Domain

The rapid expansion of the commercial space sector and the growing list of emerging spacefaring nations drive a need to understand the development of the domain as a whole. The network analysis demonstrated in this study, for example, does not provide us with an understanding of the congested space domain and the risks associated with it or how this development will continue as we do not couple it to any underlying physical or statistical model. Instead, this descriptive network analysis provides a way to visualize the entire domain as it pertains to one aspect, in this case trade and how it develops over time. Provided this could be coupled to an economic model it is plausible that this could be used to define proxies that act as precursors for how the market would continue. It is clear that these descriptive measure show 2014 to be a period of change for the space trade network. Furthermore, the rapid commercial growth in the earth observation sector has been described as unstable in its financial underpinning and heavily reliant on government investments [28]. Linking our analysis to indicators of global stability could provide further insight into the coupling between space trade and its implications. Similarly, linking our analysis with factors affecting international trade such as trade agreements and sanctions could likely provide another layer of understanding as that of 2014 and the subsequent sanctions imposed on Russia. Nevertheless, it is important to point out that network analysis, does not in itself provide, information on the intentions or inclinations of actors within space.

Recent studies demonstrate network analysis performed on multi- and bilateral agreements within space [7, 8, 10]. One noteworthy example on this front is the work by Borowitz[9] that, although it studies agreements relating to SSA data sharing, uses open source news publications to establish links within the SSA sector. Even though there are many interesting aspects to draw from these works, other studies have stated some limitations in performing network analysis on international agreements. Foremost that these type of agreements tend to be static, i.e. it is rare for a country to withdraw from an agreement once it has been signed [29]. Notably, some states have recently been seen to withdraw from the moon treaty [30], however in general this statements appears to hold true. It is therefore, in our opinion, important to consider what activity based metrics and data, regarding space actors, are available in order to fully study the dynamics of the domain. In this study, we hope that we have demonstrated that using trade is one such data, and that social network analysis on trade data can provide valuable insights for decision makers.

5.4 Future Work

Our study represents the first step, to our knowledge, of studying the space domain with network analysis on this type of dataset. Thus, several options remain in exploring, analysing and understanding the data.

We define communities in our networks but with little further exploration of their properties over time. The actors included within them and community properties such as size and density remain unexplored and require further study.

Additionally, a dedicated study of the emerging spacefaring nations such as that of Africa or Latin America would provide added clarity on the establishment of commercial space sector on their respective continents. Our analysis, at a first glance with the exception of Argentina and Brazil, sees little growth from the countries of Latin America.

Finally, this method has been demonstrated on a dataset based on international trade. We argue that further research is warranted, particularly looking at other space related datasets containing activity based metrics, to understand and characterize the space domain. One such way would be studying the satellite systems themselves and their associated countries.

6 Conclusions

Our study into the space domain applying social network analysis on international space trade have generated the following conclusions about the space domain itself and on the application of social network analysis as a whole:

- We present a novel approach in studying the space domain by combining social network analysis and international trade within the space sector.
- Our approach is not confined to the space domain, or to international trade, but should be applicable to other suitable datasets.
- The number of actors, links and the density within our longitudinal space trade graphs have significantly increased compared to that of 20 years prior.
- Space trade is evolving to an increasingly multipolar network with several well-connected actors. Using our approach, we identify the time period surrounding 2014 as one of change within international space trade. The subsequent period, starting in 2015, has been the one of establishment of a new order and growth within the space trade network and significantly more actors are now starting to participate in space trade.
- The United Kingdom exhibits a rapid increase in degree centrality and now ranks as the state actor with the most space trade connections considering the period of 2021 – 2023. However, the network at large, when considering the magnitude of trade, has been dominated by France and the US assuming alternating roles as highly ranking authorities and hubs with one exception. The period 2008 – 2014 sees Russia rank highest using the authority measure. This period abruptly ends coinciding with the annexation of Crimea.
- Social network analysis and graph theory appears well suited for studying the actors of the space domain and to understand the trends for individual actors and the domain as a whole. Network analysis highlights trends and the existing state within the domain, which reveals further paths of enquiry but does not, in itself, provide the reasons, or intentions, for these events occurring. As such, it is important to pair this with other methods and an established domain expertise to understand and interpret the results.

Acknowledgments. The authors would like to express their gratitude for the encouraging support and discussions from our fellow colleagues and researchers Joel Brynielsson, Tove Gustavi, Per Olsson and Arvid Bergsten based on their knowledge and experience in using social network analysis, graph theory and understanding of international trade.

Disclosure of Interests. The authors declare no conflicts of interest.

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