EPPS 6356.501:

Final Project - Relations Between Arms Transfers and Trade

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Introduction and Background

The dependent variable in this study is the 'TII' which basically measures how much trade is conducted between a supplier and a recipient country. Previous literature throws light on the complementary perspectives of military expenditure, international trade, economic growth, and geopolitical factors. Collectively, these pieces of writing draw attention to the public use of funds, in particular, the military field, which is now tied to global security dynamics and the regional economic sphere. By looking at different facets of these issues, the findings form a great story that connects military trade to the overall economy, thus showing the varied ways in which politics, the economy, and security interact with each other.

Callado-Munoz et. Al (2023) as well as Klare (1996), both stress that military spending and arms trade have a significant role in the economy, but their directions and scope are not the same. Callado-Munoz et al. take on the direct link between the U.S. military exports to labor productivity and the inclusion of the economic effects of military exports on growth. Besides, the geopolitics of these exports are also an area of their research that they focus on. They claim that the main channel of military exports affecting U.S. growth is direct, implying that growth mainly comes from military exports instead of the other way around. This is in sharp contrast to Klare's (1996) broader look at the global arms trade, which includes both the developments and the results of it since the Cold War in terms of stability and security in the regions. The break lines in the arms trade flows find the biggest role of moving arms not only to Asia and the Middle East but Berlin and beyond. Furthermore, the arms race in a more regional context would have a higher likelihood of ending in conflicts.

Although Callado-Munoz et al. (2023) deal with the economic aftermath of military exports, Klare concentrates on the geopolitical and security issues caused by the global arms trade. The central issue of their studies is that the army spending is inseparable from economic development, one from the economic impact and the other from the geopolitical angle.

Moreover, Malizard (2016) and Wang and Tao (2024) have furthered the debate by adding the role of public expenditure and political relationships in economic performance to the picture. Malizard's analysis of the fiscal consequences of military versus civilian spending in the EU15 provides detailed insights into how differences in public expenditure affect economic growth in the long term. Malizard employs growth theory and panel data to discover that military spending, despite being still a negative factor, has a lesser negative impact on economic growth than civilian spending. In this, he agrees with Callado-Muñoza et al. in that both studies conclude that military expenditures are less harmful to growth than the other forms of public spending. Nevertheless, Malizard's Europe-wide analysis alongside the economic crisis' impact highlights the fiscal consolidation process.

Thus, overcoming the predicament of maintaining security and fiscal responsibility during an economic downturn. While the first example is based on the fiscal policy of the EU, the second one is drawn from the new Chinese-ASEAN political relations. Wang and Tao (2024) redirect the attention to the economic aftermath of diplomatic and political relations mainly between China and ASEAN countries. By using the gravity model and event data analysis, they establish that the changes in the relations between the two regions are associated with the highest level of growth in Chinese exports. The primary reason for their analysis is the fact that mutual political stability and trust are the key elements for economic growth, which indicates that strong diplomatic ties are a prerequisite for long-term trade relations. In a way, their results can be seen as an argument for Klare's view that arms sales and more generally geopolitical factors have important impacts on economic outcomes.

Summing up, the four studies together are a repetition of the fact that political and military factors cannot be separated from economic growth. Callado-Muñoza et al. and Klare both focus on the effects of the defense budget and arms sales on the economic outcomes in the case of the first and the second one, while Malizard and Wang and Tao broaden the perspective by investigating how public spending and political relations in general affect the growth of the economy and trade. The four studies said the same thing: The military and international relations are not only the main issues of global security, but they also are very closely linked with the economic factors that cause the nations to get rich. It is the picture that the conditions that enable world peace are not only the military expenditures and arms trade but also the political alliances that are of paramount importance for the economic development of the world.

On the one hand, these studies are methodologically and perspective-wise very different from one another. Callado-Muñoza et al. and Klare look at the broader and geopolitical perspectives, while Malizard and Wang and Tao focus on the local issues and how public expenditure and diplomatic relations are affected. At the same time, all four papers clearly show the agreement that military and political factors have a significant impact on the economy, however, the nature of the impact may be different in different contexts. The four studies, by pulling together different perspectives, deepen our understanding of how military trade, public spending, and political relations shape global and regional economies.

As for the independent variable in our study which is the arms exports pattern Yakovlev (2007) examines the research question if military expenditure and weapons trade be growth inhibitors, or can their interaction foster the economy? The focus of this research study is on the latter. The scholar gathered data from twenty-eight countries across various periods from 1965 to 2000 by employing different statistical techniques to analyze the relationship between military spending and arms trade on the economic performance of the countries. The research papers show that generally both armament expenditure and becoming a net arms exporter are related to the decreasing economic growth of a country.

Nevertheless, the study divulges a crucial piece of information as well: military spending is tolerable to a certain extent in countries that are also net arms exporters. This then implies that countries that sell more arms to other nations will likely maintain or even increase their military budgets without the negative impact on their economy like those that don't engage in arms exports. It is also noted that selling arms is one of the financial advantages that can relieve the economy from the cost of high military spending. Conversely, for countries whose weapon industries are not thriving, military spending is the most specific cause of stagnating economic growth. In conclusion, the study supports the confusing and unpredictable interactions between military spending, arms trade, and economic growth as well as stresses the ability of a country acting as an arms exporter to cushion some of the adverse effects of military spending on its economic standing. Anthony and Stockholm (1998, 93-106) find that the Soviet and Russian arms exports analysis has shown that arms sales have brought remarkable financial benefits to the central state, but profit was not so clear for the manufacturing enterprises.

In the Soviet period, the arms production system was mainly set up for military uses. The expenses relating to export production were only minimal. Arms exports were actually the means through which the Soviet Union was able to get certain goods and foreign currency that could not be obtained otherwise. Nevertheless, the exact amount of foreign currency that accrued from arms sales is still uncertain owing to incomplete data and barter and non-cash payment usage. As the Cold War ended, the most noticeable change in Russian arms trade was the companies that, in most cases, preferred the foreign market rather than the home one, especially for complex systems, though this did not necessarily improve the Russian economy. Price control, subsidies, and the weak ruble caused the weaknesses to worsen, and competition in the post-Cold war arms market also posed a challenge for successful exports. Besides, the weapons transfers to the Caucasus (CIS) states were amongst Russia's measures to form defense cooperation.

This could imply that countries with higher arms exports might show stronger trade relationships (reflected by higher TIIs) with their partner nations, which would support the idea that arms exports positively influence trade intensity. Anthony's (1998, 93-106) research of Soviet and Russian arms exports contends that while sales of arms were useful for enhancing the center's grip on the nation, the wider economic implication remains still complex due to factors such as price controls, subsidies, and post-Cold War market competition. Even though they encounter such challenges, Russia's commitment to international export activities over the domestic market, notably for high-tech systems, might develop this TIIs for mutual defense agreements, mainly with those countries which are partners in economic development or defense cooperation through the sale of military equipment. Both studies state that the arms exported would play a bigger role in trade intensity.

Furthermore, the armament exporting countries, which are basically the leading exporters of weapons, are often the countries that have maintained very strong trade relations. This could either be direct sales or through indirect, non-cash means of trade. They almost have the same experience by saying that both weapons exportation and military expenditure have less obvious effects on economic growing and trading because a good dataset that links 'TII's between arms-exporting countries and trading partners would help a lot. The hypothesis that arms exports influence 'TII's, in fact specifically, the type of weapons that are part of the arms transfer has an impact on the 'TII's.

Research Question

We focus on the differences in arms-giving patterns between ‘Russia’, ‘China’, and the ‘U.S.’ and select recipients of each of their arms for the years covering 1996-2022 (see below). We will use association-mining rules (‘ARCs’) to *estimate* the probabilities that certain types of weapons are liable to be transferred with others and ascertain whether this correlates with the status those ‘supplier’ nations have with various ‘partner’ nations as measured via a Trade-Intensity Index (‘TII’) metric that holds between them any given year.

Data Collection

We gathered bilateral weapons ‘Import/Export Values’ transfer data from the Stockholm International Peace Research Institute (SIPRI) ‘Arms Transfer Database’ for the years spanning from 1992 to 2022 (SIPRIa n.d., ‘SIPRI databases’). Specifically, we pulled the values of the weapons transferred between countries for those years as a single .csv file. From the World Bank’s ‘World Integrated Trade Solution’ (WITS) database we gathered bilateral trade (import and export) level-data between our nations of interest, and for the entire globe, for the same year span as a series of .xlsx files (World Bank 2024).

As noted above, we aim here to focus on the relations between the ‘supplier’ nations of ‘Russia’, ‘China’, and the ‘United States’ and the ‘partner’ nations of ‘Afghanistan, Belarus, Bangladesh, India, Iran, Iraq, Israel, Japan, Myanmar, Pakistan, Qatar, Saudi Arabia and South Korea’. We used the ‘Pandas’ package in Python (McKinney and Python Dev. Team 2022) and various data wrangling tools in Microsoft Excel in order to filter, pivot and merge our separate datasets into a single easy-to-use ‘tidy-format’ (long-form) .csv file suitable for subsequent visualization and analysis tasks.

However, we did not have overlap between all bilateral relationships for all years. Particularly, Russian trade data was only available for 1996 onwards. Further, trade data for most countries in our custom data-set only spans to 2021 for the majority of cases and only up to 2017 in the cases of Russia's relations with 'South Korea', 'Iran', and 'Egypt'.

Exploration with Data Visualizations

To best understand our data set, we decided to adhere to the principal heuristic outfitted by Alberto Cario as '*Candid Communication*': that the goal to be served by data visuals "…is to enlighten people." (Cario 2016, 13). We adopt the approach that statistical charts in particular should serve the purpose of illuminating either the composition, relationships, distributions, or comparative facets of the variables that make up a dataset (Abela 2010, 36).

A variety of packages were used in construction of these graphics. Heavy use was made of 'ggplot2' (Wickham 2016). The thematic ggplot2 extension packages 'ggthemes' (Arnold 2024) and 'ggdark' (Grantham 2022) were also incorporated into our code. The 'patchwork' (Pedersen 2024) package was used to combine selected graphs together, and the 'dplyr' (2016, 207), 'tidyverse' (Wickham 2023), and 'naniar' (Tierney et al. 2024) packages were used for data filtering.

Beginning with trade data, we can plot the 'Import' and 'Export' relationships between our 'Supplier' countries and their 'Partner' nations ('Figure 1'). We can see that trade flows rose for each 'Supplier' country over time, although particularly in the cases of the 'U.S.' and 'China'. Looking at the scatter-chart in 'Figure 2', the overall trend in increasing bilateral trade becomes even more apparent, although the relationships with 'partner' nations is not explored in this graphic.

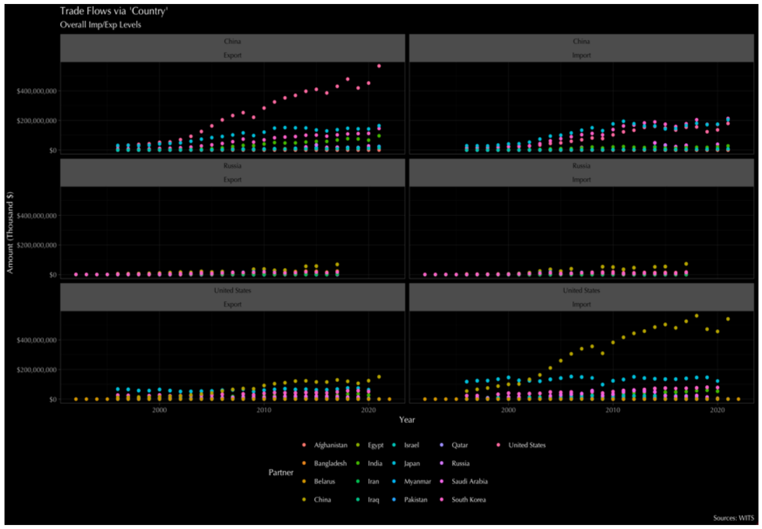

Figure 1

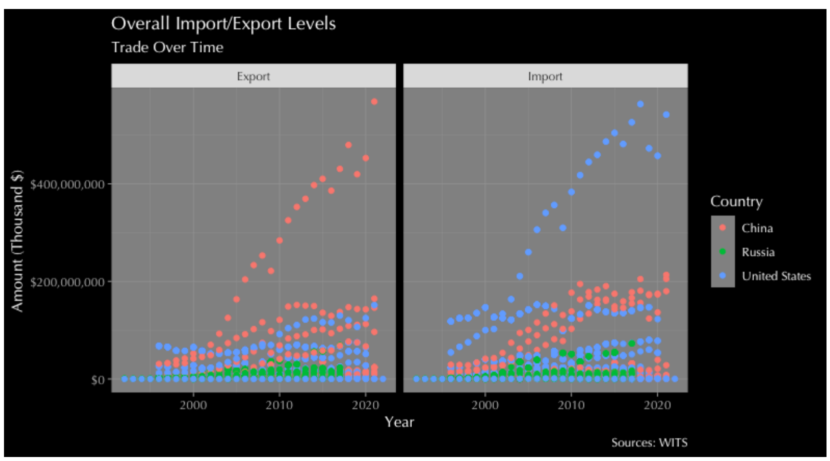

Figure 2

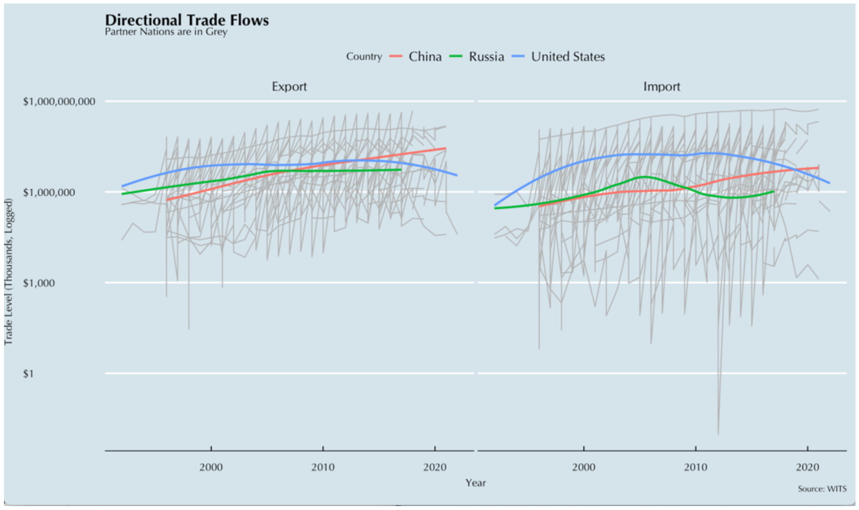

Figure 3

The trendline-graphics in 'Figure 3' allows us to get a sense of the 'supplier' nations trade growth by observing the levels of trade, per flow ('Import' or 'Export'), per year on a logged y-axis. In both 'Figure 2' and 'Figure 3', it becomes clear that 'U.S.' import and export levels have fallen recently. 'China' has steadily risen, while 'Russia' has fluctuated. Another observation of note is how low the volumes of trade are with respect to 'Russia'. In fact, it appears that Russia's most significant trading partner is 'Belarus'. While the United States's most significant trading partner by volume is 'China', and China's is the 'United States'.

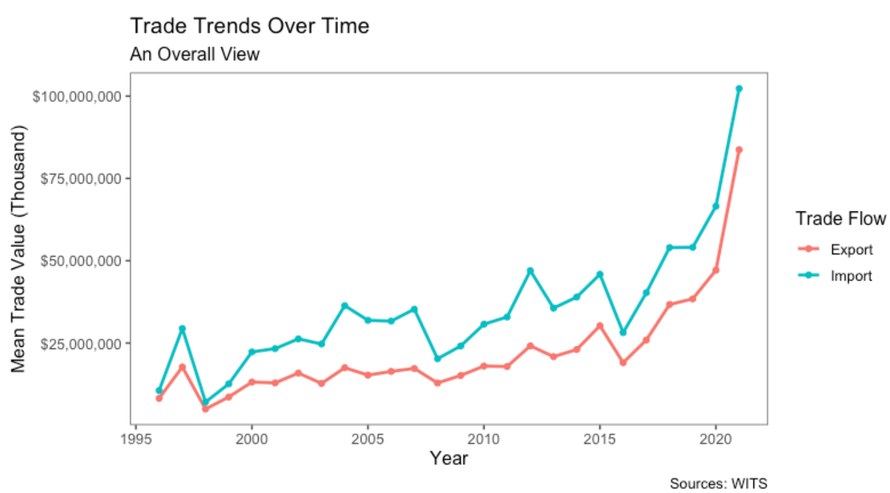

Figure 4

‘Figure 4’ again plots the trend of export and import levels over the timespan of our dataset. It is even clearer from this graph that *overall* trade volumes between the countries under consideration in our study have been rising over the timespan of our study.

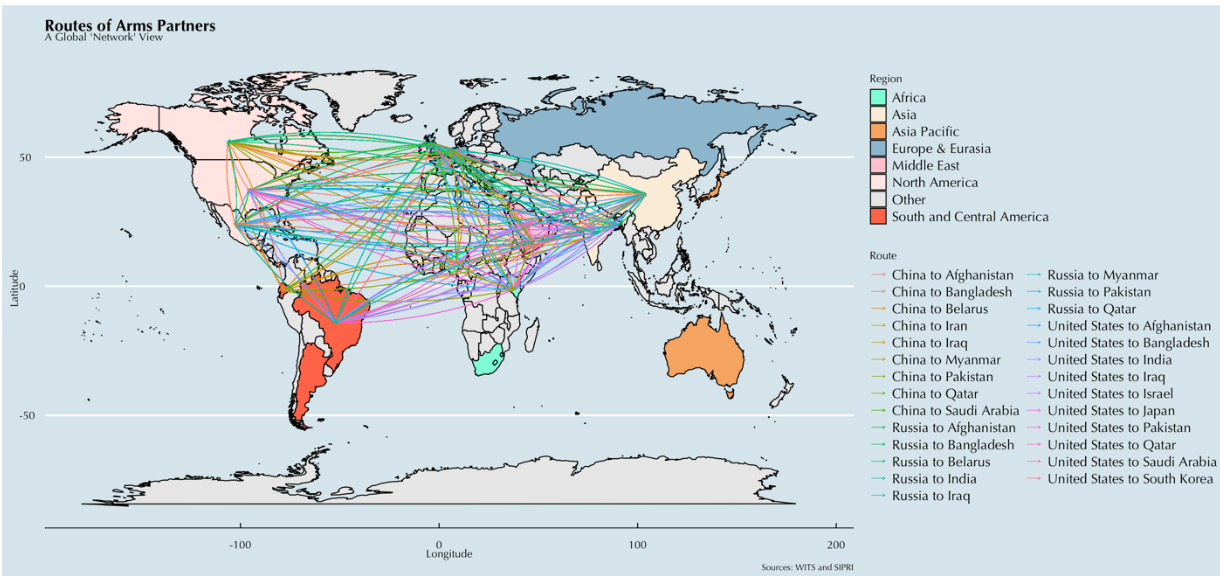

Figure 5

In ‘Figure 5’, we used ChatGPT 3.5 (Hua et al. 2023) to assist us in utilizing the ‘maps’ (Becker et al. 2024) and ‘tibble’ (Müller et al. 2023) packages to make a world map of the linkages of our arms-partnerships. Such a map graphic helps to make intuitive the geographic proximities and connections of the nations under consideration in this study. See our GitHub repository for the ‘EPPS 6356_Team Maitreyi - Final Project Materials’ directory for ChatGPT chat-logs (Merrill 2024).

Another lens through which to examine trade is via the ‘Trade Intensity index’ or TII. This is a metric that measures how intense the trade between any two countries is at a certain point in time (Wang and Tao 2024, 9). Specifically, the TII compares the export levels of two countries to world-wide export trends to calculate a ratio that that varies between 0, and any number greater than 1: A ratio of '1' represents an expected level trade between a random sampling of two countries at a given point in time; a ratio higher or lower than '1' represents a greater or lesser intensity of trade than that which usually transpires between two nations at a given point in time (World Bank 2010). The 'TII' ratio is specifically: "$T_{ij} = (x_{ij}/X_{it})/(x_{wj}/X_{wt})$, where x_{ij} and x_{wj} are the values of country i's exports and of world exports to country j and where X_{it} and X_{wt} are country i's total exports and total world exports respectively." (World Bank 2010).

Calculating the 'TII' and plotting the scatter-relationship between the nations in our custom dataset in 'Figure 7' reveals that for most countries, the 'TII' between them is often only of a rank of close to '1', as expected. But the exceptions are interesting: China seems to often have high 'TII' score with 'Myanmar', the United States has such a relationship with 'Israel', and, again, Russia with 'Belarus'. We can also break down the national relations of 'TII' by year. Faceting via 'year' in 'Figure 8' makes clear the outliers in 'TII' rank on a yearly basis. It is worth noting that the 'TII' between the 'U.S.' and 'China' are not the highest for either nation via this metric. This indicates they have both been trading a lot with other nations than just each other, and that these relationships also explain the rise both have experienced in trade volumes since 2000.

There is a trend observable for these graphics: many 'supplier' nations have relatively more intense trade relationships with those 'partners' of close geographic proximity and/or apparent political-cultural disposition. What is worth remarking upon, however, is the relative trade *levels* of the largest trade actors in our dataset, and the fact that their relationship does not fit such a mold: e.g. the trade relationship between the 'U.S.' and 'China' since 2000.

‘Figure 6’ allows us a quick glance at the distribution of a slice of ‘TII’ ranks across our dataset via a proportional kernel-density graph. The red line illustrates where the average ‘TII’ rank of ‘1.67’ stands in relation to most proportional ranges of ‘TII’ ranks.

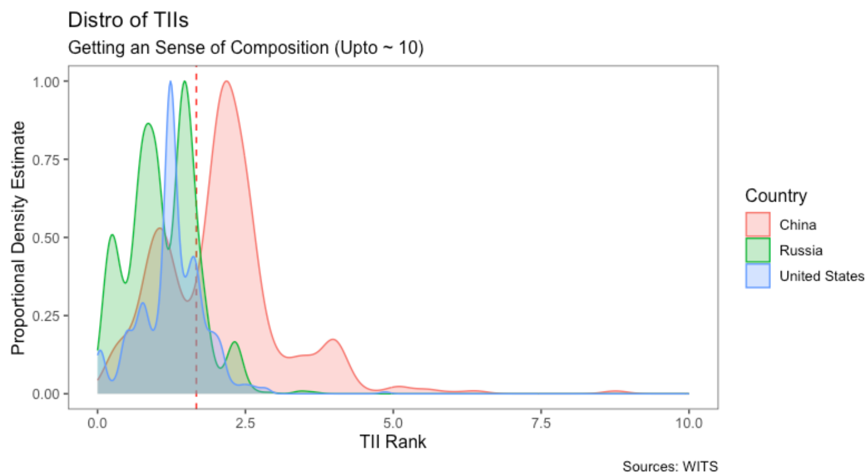

Figure 6

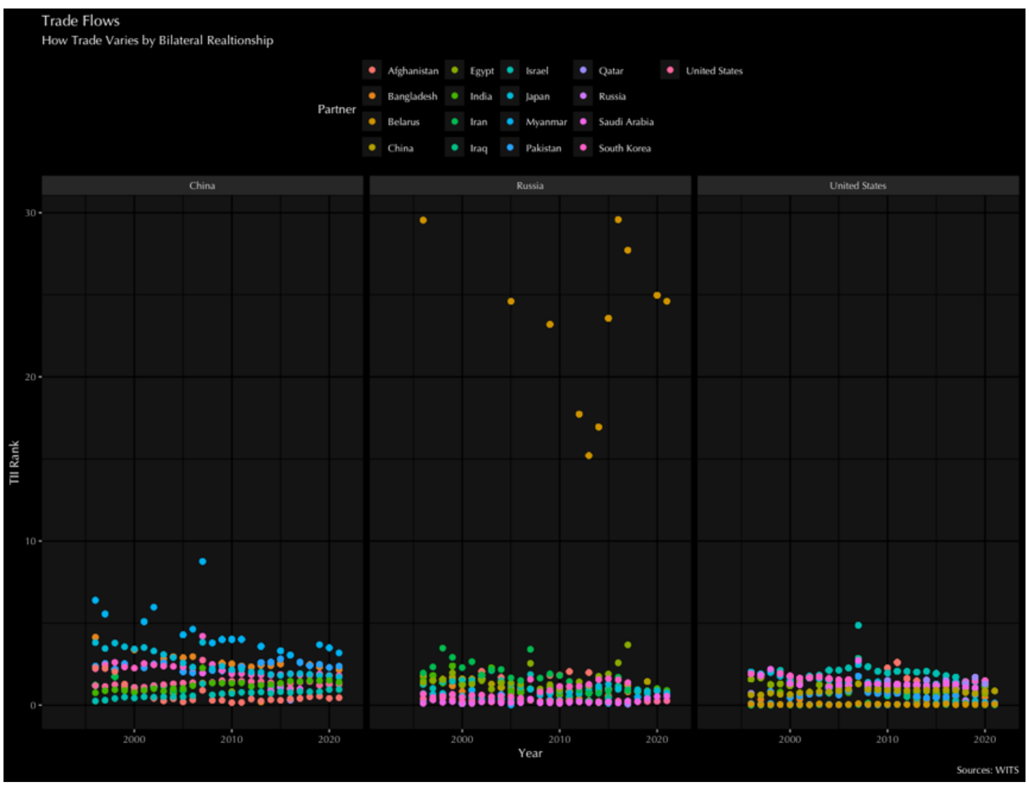

Figure 7

Moving onto arms analysis, examining the weapons transfer data extracted from ‘SIPRI’ will allow us a view of the other key component of our dataset. Looking at the stacked bar-chart in ‘Figure 10’ let’s us breakdown the frequency of the type of armament transferred, and the *relative* proportions of which country supplied them. We see ‘missiles’, ‘aircraft’, and ‘armored vehicles’ make up the bulk of transferred weapon types. We can also see that the U.S. supplied the bulk of every weapon type except ‘air defense systems’.

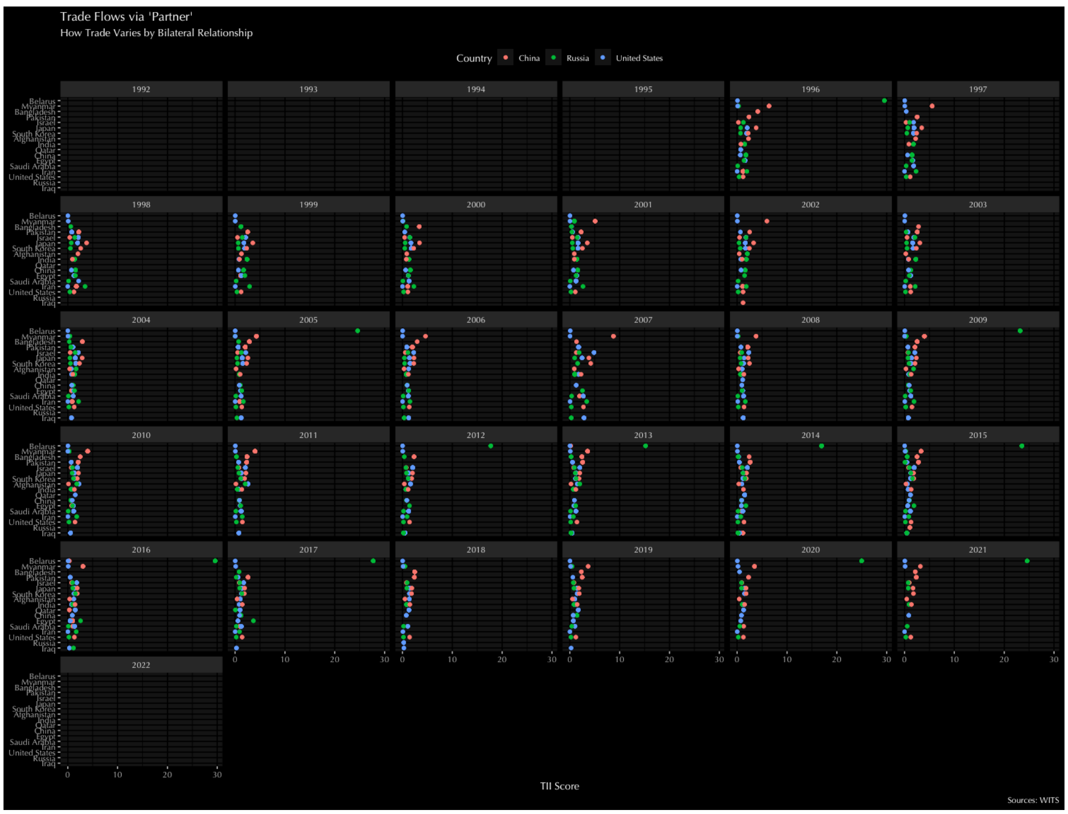

Figure 8

Our dataset comes with a metric designed to measure weapons transfers over time known as ‘Trend-Indicator Value’ or ‘TIV’. Specifically, the ‘TIV’ *estimated upon weapon delivery*. This metric allows the comparisons of weapons trends over timespans and is not directly based on the financial value of the weapons transferred (SIPRIb n.d., ‘Sources and methods’). It is akin to a proxy-cost measurement. ‘Figure 9’ plots a random subset of the top trades as measure via ‘TIV’ over the entire timespan captured in our dataset. It allows us a glance at some of our data’s most prominent arm relationships: that between the U.S. and South Korea, China and Pakistan, and Russia and China stand out particularly starkly. We can examine the change in ‘TIV’ values over time with the scatter-charts in ‘Figure 12’.

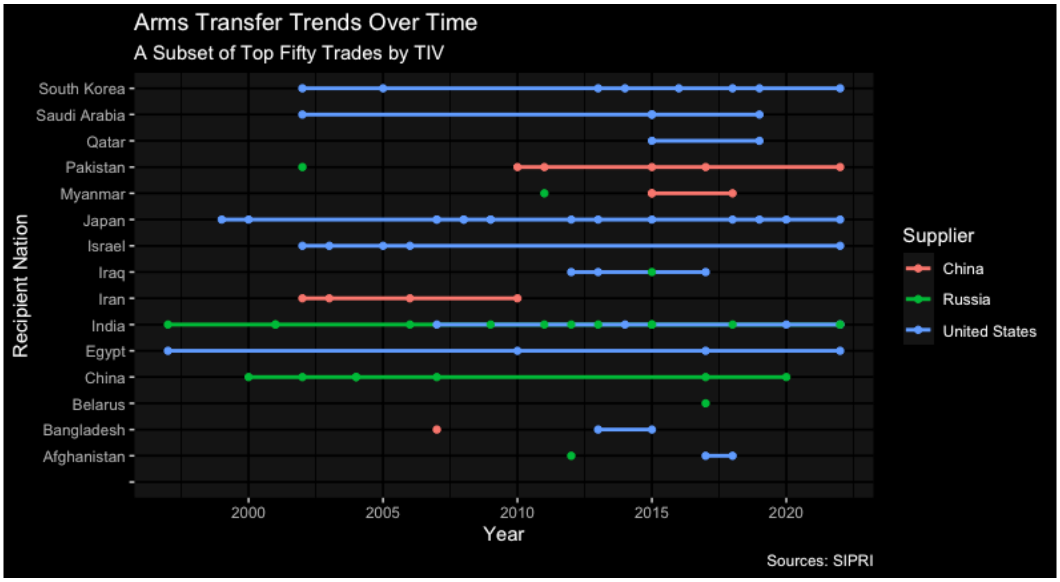

Figure 9

We can see the distribution of ‘TIV’ scores for a subset of our data in ‘Figure 11’. A kernel density graph, the blue-line marks the mean ‘TIV’ value of 59.38.

Further, we also can compare the distribution of weapon type via ‘TII’ and ‘TIV’ scores with the help of boxplots in ‘Figure 13’. This allows us to see that most of the weapon types are distributed within the ‘sub-300’ ‘TIV’ range and are associated within normal ranges of ‘TII’ ranks. Although plenty of outlier transfers certainly exist.

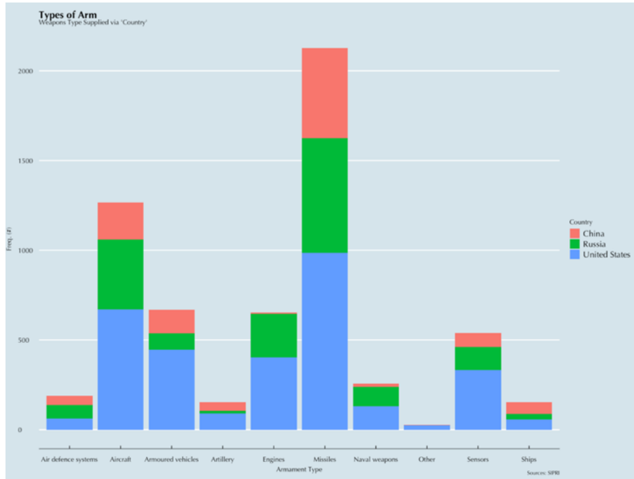

Figure 10

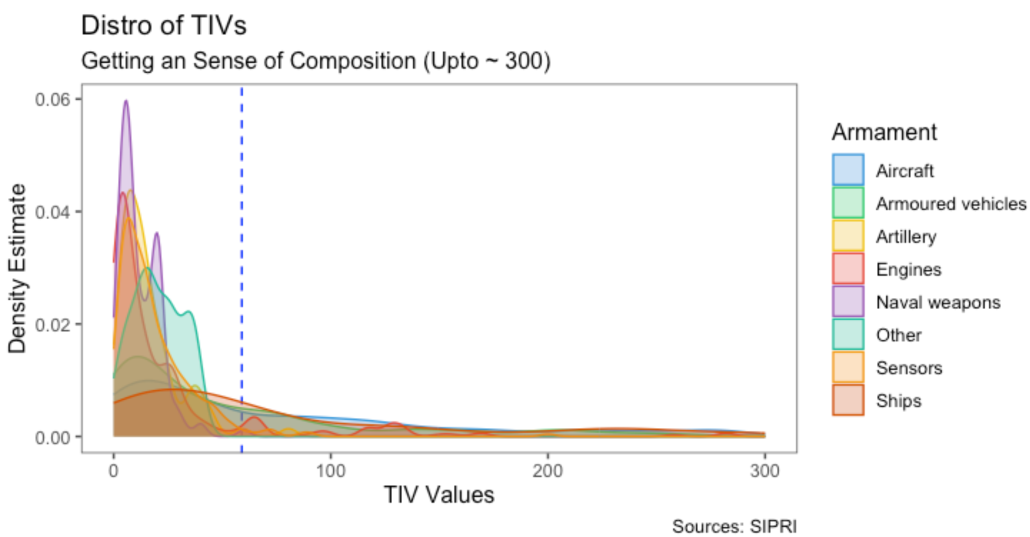

Figure 11

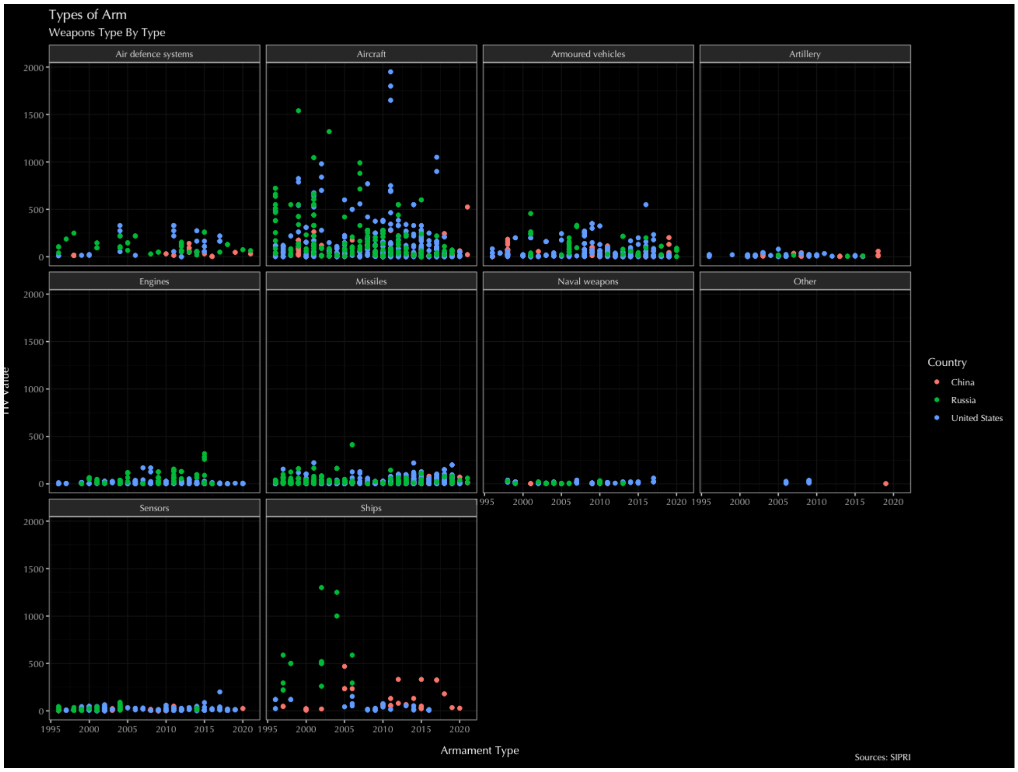

Figure 12

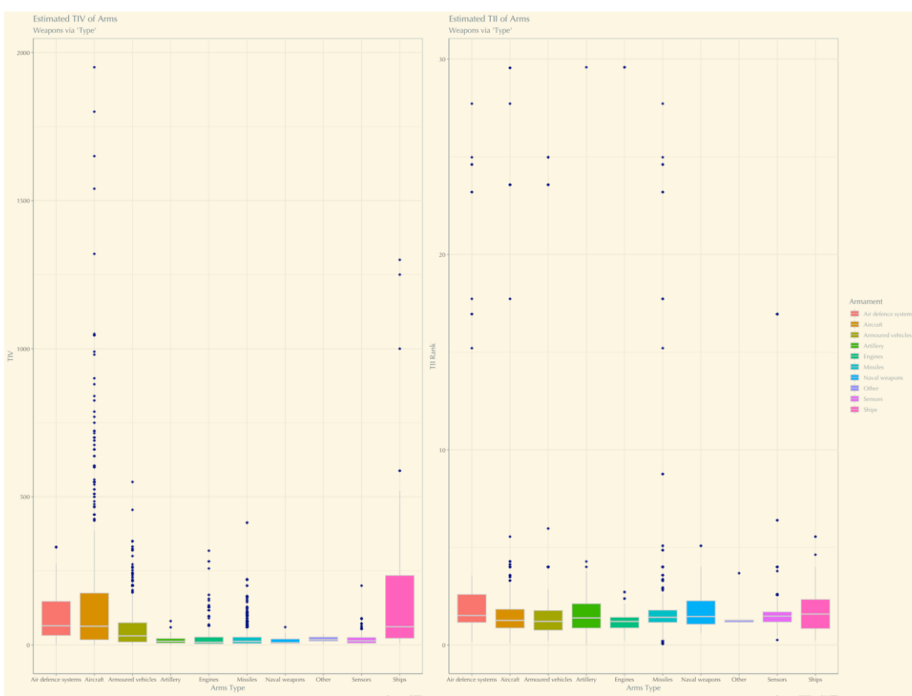

Figure 13

Visuals constructed with the aid of the ‘ggbeeswarm’ package (Clarke et al. 2023), ‘Figure 14’, which focuses on the three most populus weapons type with ‘bee plots’, emphasizes the observation that the U.S. and Russia are the largest supplier of weapons in our dataset. We can see that ‘Aircraft’ spans the widest range of ‘TIV’ values. To focus on what ‘partner’ nations receive what type of arms from which ‘supplier’ country, ‘Figure 14’ indicates that the U.S. has conducted its highest valued (per ‘TIV’) transfers with ‘Saudi Arabia’, China has done so with ‘Pakistan’, and Russia with ‘China’. The red line marks the mean ‘TIV’ value of 58.87.

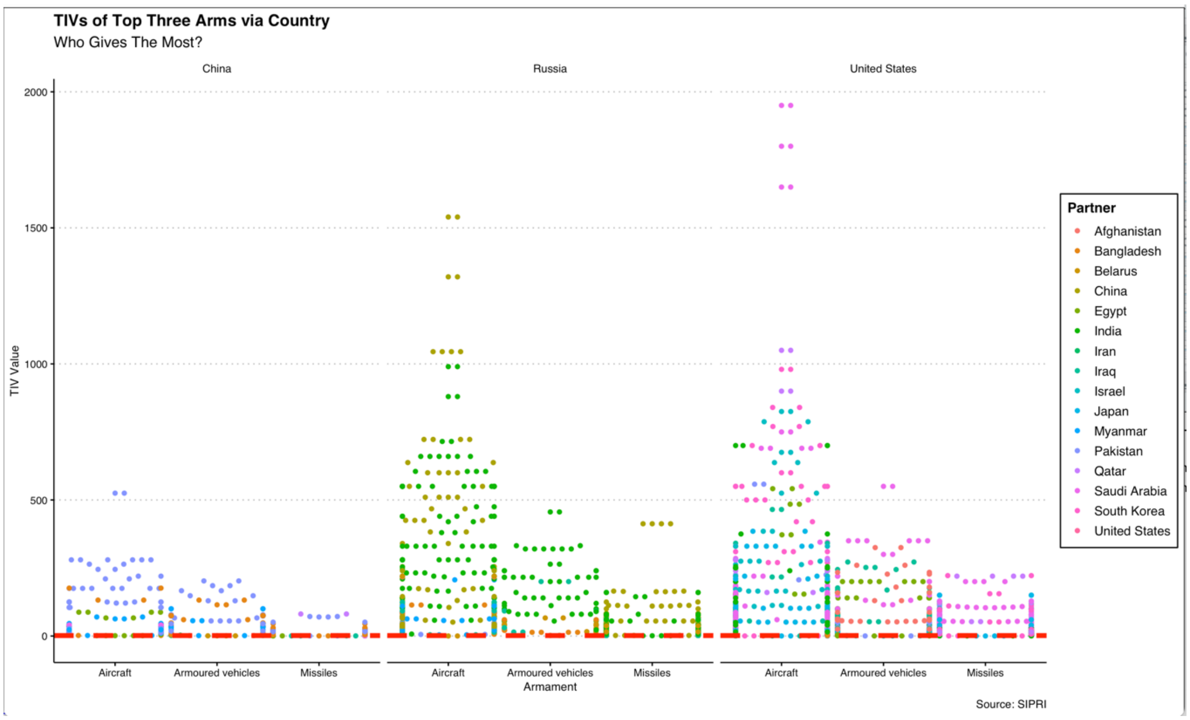

Figure 14

To get a perspective on how ‘TIV’ and ‘TII’ scores compare to each other, we can make use of a 2d-density plot, as shown in ‘Figure 15’. This shows that ‘TII’ ranks between ‘1’ and ‘1.5’ correlate with ‘TIV’ scores under ‘20’ most intensely.

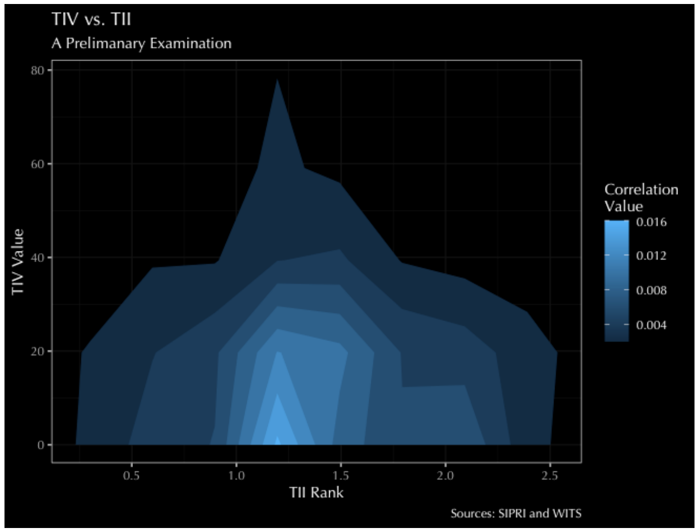

Figure 15

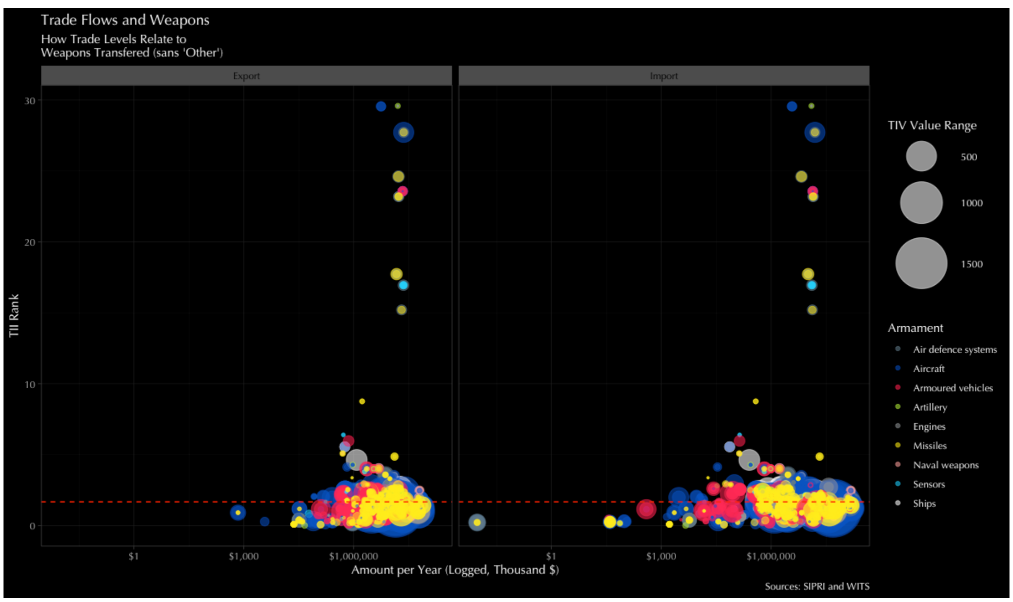

Figure 16

Plotting the relation between trade levels, ‘TII’ rank, ‘TIV’ values and arms type via a bubble plot in ‘Figure 16’ shows the *interconnections* more clearly. We can see that the most common weapons transferred were ‘aircraft’ and ‘missiles’ at a normal ‘TII’ rank. The red lines point out the average ‘TII’ rank of ‘1.67’.

We can also see, with ‘Figure 17’, that a high ‘TII’ rank is associated with transfers of ‘aircraft’ and ‘missiles’ in the case of Russia, ‘missiles’ and ‘aircraft’ (slightly) in the case of the U.S., while ‘missiles’ stand out most prominently in the case of China. Additionally, in each of these cases the value of the transfers as measured via ‘TIV’ scores is not massive. The red lines again denote the average ‘TII’ rank of ‘1.67’.

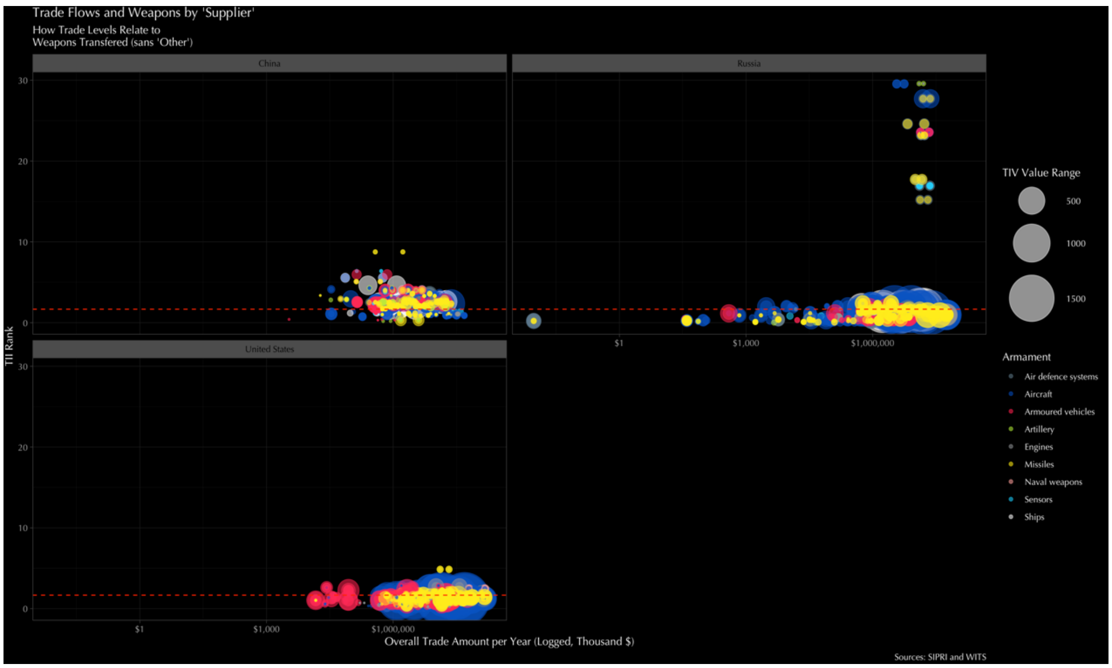

Figure 17

For a wholistic perspective of *overall* non-directional trade flows and weapon transfers we can examine network plots of each of those facets of our dataset in ‘Figure 16’ and ‘Figure 17’, respectively. These plots, constructed with the ‘igraph’ package (Csárdi et al. 2024), allow us to see the strength of various bilateral relationships in our dataset. Such as the strong trade relations between ‘Russia’ and ‘Belarus’, and the fact that the arms relations between the ‘U.S’. and ‘Qatar’ and ‘Israel’ are more voluminous than that between the ‘U.S.’ and ‘South Korea’.

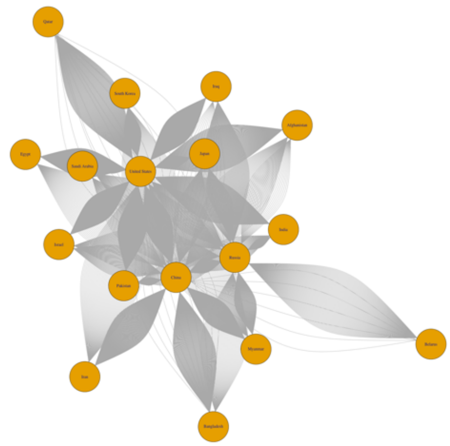

Figure 18 (Trade)

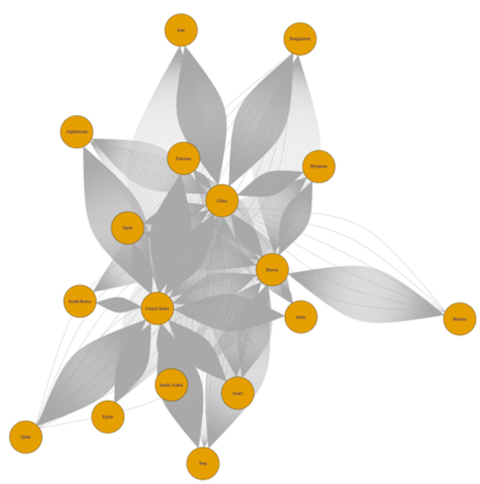

Figure 19 (Arms)

The most salient aspect of our dataset brought out by this network perspective is that the same partner countries that have the highest ‘TII’ rank with one another do not necessarily trade the most in weapons as measured via ‘TIV’ scores.

Association-Rules Modeling

Our research design is focused on finding patterns between two-countries’ weapons transfer ‘bundles’ as found via ‘association-rules based’ modeling and their ‘TII’ rank.

Association Rules Classification (ARC) is a statistical technique used to describe how frequently items that can appear within 'transactions formatted registers' of many different 'baskets' of goods appear in the same 'baskets' as one another: a technique originally developed to analyze retail sales patterns (Kirenz 2023). More poignantly, ARC can be used to *estimate* the conditional probability that a given item will be 'bundled' with other item(s) given a particular dataset (Attewell et al. 2015, 227-229, Hahsler et al. 2017, 254-255).

A slate of standard thresholds denoted as 'support', 'confidence' and 'lift' are calculated to select a reasonable combination of values that are most likely to allow insight into associations between items within a given dataset (2023). The 'confidence' and 'lift' metrics are each built upon the 'support' metric, which measures how frequently an item combination appears (2023). There are a number of ways to 'tune' combinations to calculate the 'support' threshold (Kliegr and Kuchař 2019), but one of the most common is to prune the least frequent item-sets in favor of more frequent ones iteratively (Vanhoof and Depaire 2010, 5). It is with such a pruning method, the 'apriori algorithm' (2023), that we implement via the 'arules' package in R (Kliegr 2023), that we conduct our analysis.

We used the 'pandas' package in python (McKinney and Python Dev. Team 2022) in order to make our SIPRI weapons data amenable to association analysis. This involved turning each possible combination of arms type into a 'true/false' matrix suitable for input into the 'apriori' function of the 'arc' package. Examining the density of 'True' and 'False' hits in our matrix revealed it to be very sparse. We therefore decided to only allow conditional pairings where the left- and right-hand sides (made of 'transaction baskets') of association rules found would hold 'true'. In order to focus on rules likely to be positively associated with most of the transfers in our dataset, we also decided to focus on parings that would result (construe the RHS) in the most commonly transferred weapon type, which was ‘aircraft’. As a category, ‘aircraft’ was a ‘true’ hit 10,080 times in our dataset, far surpassing all other arms categories, the next highest of which was ‘missiles’ with 848 hits.

Settling on a ‘support’ and ‘confidence’ threshold of .05% each resulted in a set of four ‘rules’. This threshold seemed to offer a manageable number of ‘rules’ to see what weapon type had a clear association with ‘aircraft’ transfers. The components (left-hand sides) of the ‘rules’ found are graphed on the uplifted x-axis of ‘Figure 20’ and around the centroid portion of ‘Figure 21’.

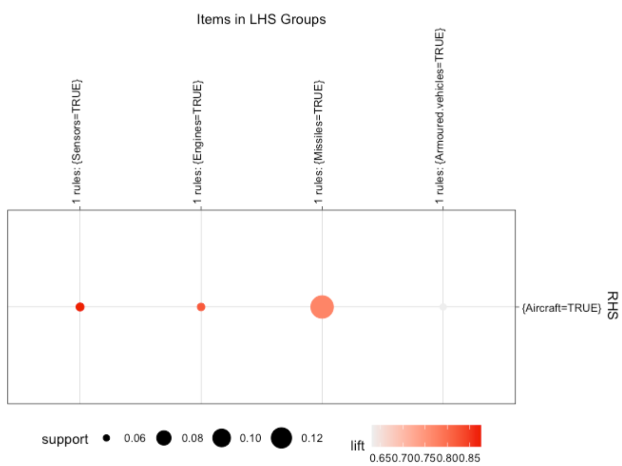

Figure 20

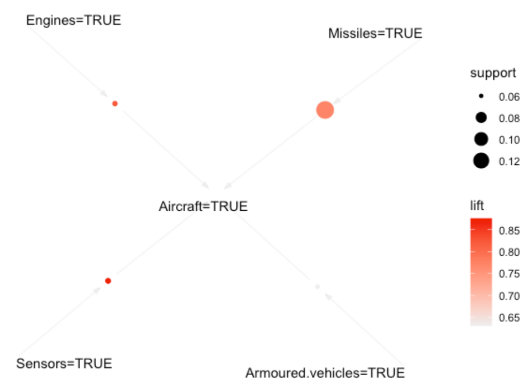

Figure 21

Our mining approach allowed us to find those rules that represented sets of arms pairings that populated *at least* .05% (our support and confidence levels) of all ‘transactions’ in our dataset. We can see from ‘Figure 21’ that by these criteria, transfers of ‘engines’, ‘sensors’, ‘armored vehicles, and ‘missiles’ were most associated with ‘aircraft’ transfers.

Comparing ARCs with TII Rank

Making a comparison of those rules that lead to ‘aircraft’ transfers and seeing if these are correlated with ‘TII’ ranks was done with the ‘ggthmer’ package (Mikata-Project 2022).

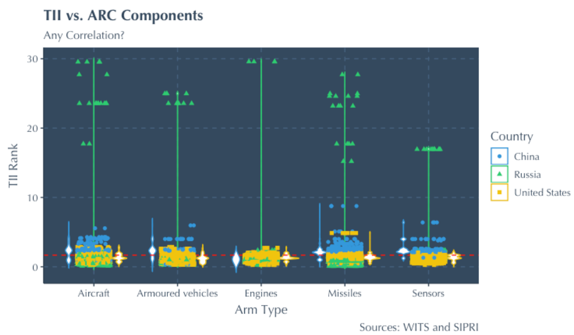

Figure 22

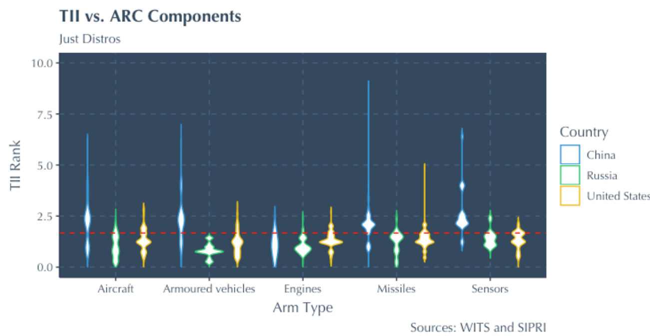

Figure 23

With the violin/strip chart in 'Figure 22', we can plot the correlation between 'TII' rank and those component armaments that make up 'bundles' with 'aircraft' transfers. Read like boxplots (Hintze and Nelson 1998, 181), the bisection midline of each 'violin' cluster represents the median 'TII' rank of the arm-supplier relationship under question. The red line at 1.6 indicates the average 'TII' rank (1.67) across our dataset.

'Figure 22' has arms reaching 'TII' ranks at their highest prevalency when 'Russia' is the 'supplier' country. However, the picture is less clear in most of the cases concerning not only 'Russia' but also 'China' and the 'U.S'. Mainly because most of the transfers of these weapons are not as a group clearly associated with strictly higher 'TII' ranks. Zooming in on just the 'violins' of ranks under 10 in 'Figure 23' reveals that Chinese arms transfers are typically associated with slightly higher 'TII' ranks than those associated with the U.S. and Russia at this range. But there is still not visually a large disbursement of median value arms correlations.

A conclusion that concords with the lack of overwhelming association of 'TII' ranks with arm type explored above ('Figure 13' and 'Figure 17'). Still, the Russian relation does suggest that the correlation *may* exist in some other circumstance, perhaps due to more subtle economic ties and/or military-cultural dynamics not explored here.

Concluding Remarks

Some real limitations of this study hinge on the fact that only select 'supplier/partner' relationships were included for correlational and ARC analysis. A major change in patterns may be expected with the inclusion of say, India, as a 'supplier' nation. Further, the inclusion of other timespans may reveal a sharper or more dispersed relationship between trade relationships as measured via the 'TII' and weapons transfers as coalesced into the 'TIV' proxy.

Further, the adoption of different modeling parameters could also change our findings. Our assumption that rules should be 'hitched' to the positive left and right-hand side outcomes with most prevalent weapons type ('aircraft') is not the only basis on which to construct association rules from this data set.

Our non-decisive finding is not the death of our hypothesis but just this particular approach to verifying it with this particular data. This hypothetical relationship, therefore, between polities is worth exploring in regard to other contexts to see if it holds more steadily. Perhaps then confidence that certain weapons transfers are likely to be associated with trade intensity can help inform policy-making apparatuses across a range of regional or national contexts.

'Plotly'-based Dashboard

In addition to the analysis conducted above, our team also developed and launched an interactive dashboard to accompany this paper. We made use of the 'plotly' (Sievert et al. 2024) and 'flexdashboard' (Aden-Buie et al. 2023) libraries to add interactivity modules to select visualizations. We also utilized the 'circlize' (Gu 2024) and 'networkD3' (Allaire et al. 2022) libraries to develop 'Sankley Graphs' that illustrate the 'flow' of trade and arms transfer relationships in our dataset. This dashboard is accessible via: https://rpubs.com/tjm3467/1251897 (Merrill 2024).

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