# External Drivers and Internal Dependencies of the International Arms Transfers Network 1993-2023: A Sequence of Temporal Exponential Random Graph Models

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## 1. Introduction

***Policy relevance.*** Global transfers of major conventional weapons (MCWs) came back as a ubiquitous issue following the Russian invasion of Ukraine on 24 February 2022. Who supplies weapons to whom, which types are provided, and how to finance them – these are questions busying governments of major powers. Thus the topic garnered extensive media and academic coverage over the past two years (Mehrl & Thurner 2025, p. 2). Moscow's attack is received as an assault on Europe's status quo security order, triggering a widespread change in perceptions about international security constellations. This prompts government to revise arms transfer policies across the world (SIPRI, 2024e, 2024f). Some of the world's largest weapons exporters, most of whom are made up by North Atlantic Treaty Organisation (NATO) members, undertook a sharp "Foreign Policy U-Turn" (Eddy 2022). Decades-long military doctrines were revised and protracted debates were started about whether to ship weapons to conflict zones, and if so, under which conditions (Eddy 2022). A remarkable example is Germany which consistently belongs to the top five arms exporters, both in terms of trade partnerships and trade volumes. It traditionally maintains military neutrality where possible and exercises utmost caution when it comes to weapon transfers to active conflict parties (Eddy 2022). Yet, three days after Russia's aggression, German Chancellor Olaf Scholz declared a "watershed moment"[1] where security is back at the center of German politics. Vowing to arm up Ukraine (Scholz in Bundesregierung 2022b), he departs from the German traditional refusal to transfer weapons to active conflict regions (Eddy 2022).

Weapons trade is not simply an exchange of goods. Worldwide arms trade patterns reflect international security constellations. (Buzan & Waever 2003, p. 216; Harkavy 1994, p. 11; Thurner et al. 2019, p. 1737) Geopolitical tensions worldwide prompted states to up their defense budget, production, and purchase capacities. Alarmed by Russia's militant actions, the NATO alliance invests in collective defense capabilities to deter future threats. At the NATO's Madrid Summit in 2022, its Secretary General Jens Stoltenberg declared the bloc would "step up support to Ukraine, [f]urther strengthen [its] deterrence and defence, [a]nd invite Finland and Sweden to become NATO members." (Stoltenberg in NATO 2022b; Stoltenberg in NATO 2022a). Worldwide, countries scramble for MCWs to counter threats – both real and perceived (Wezeman et al. 2024, p. 1). Overall, 2023 marks the ninth unbroken year-on-year rise in global defense spending. The 2023 growth rate of 6.8 percent is the highest recorded since 2009, and

[1] Original expression "Zeitenwende"

with a sum of $2443 billion, the year 2023 also marks the largest absolute spending level registered since 1949 (Tian 2024, p.1).

This huge sum was fed into the global arms market of the past 3 years. On the demand side, Europe's 5-years arms import average rose by 94 percent between 2014-2018 and 2019-2023. Countries in Asia, Oceania, and the Middle East are the main buyers, with 9 out of the top 10 importers in 2019-2023 hailing from these regions (Wezeman et al. 2024, p. 1). Ukraine rose to the 4th place in the import ranking since outbreak of war after obtaining MCWs from more than 30 states in 2022 (Wezeman et al. 2024, p. 2). In the same year, Russia's imports decreased by over 50 percent (Wezeman et al. 2024, p. 1). This is likely because members of the NATO bloc – together providing ca. 70 percent of global exports (Wezeman et al. 2024, p. 1) – stopped selling to Russia. On the supply side, the 5-years arms export average of the world's top producer, the United States, increased by 17 percent between 2014-2018 and 2019-2023. The second largest exporter, France, increased its sales by 47 percent. In 2019-2023, the top 5 exporters are the USA, France, Russia, China, and Germany – together providing 75 percent of global exports. (Wezeman et al. 2024, p. 1) Overall, these statistics demonstrate the policy relevance of arms trade yet again (Mehrl & Thurner 2025, p. 2).

***Academic relevance***. The arms transfer market is not only relevant to policy makers, but also to the discipline of international relations and political economy (Buzan & Waever 2003, p. 216; Harkavy 1994, p. 11) Global arms transfer patterns map developments in international politics, such as policy preferences, interstate relationships, and the overall "hard power" distribution in the system (Willardson 2013, p. 5).

Thanks to latest advances in network analytical methods and improved availability of computing power, new trajectories in arms trade research opened up. The application of inferential network models to investigate international arms trade gained traction after Thurner and his colleagues presented their seminal paper in 2019. It is the first to suggest a network theoretical framework to explain global arms trade, and is also the first to apply an inferential network model to test its theoretical propositions. These models are able to capture the effects of external drivers on arms transactions while controlling for internal network dependencies, including temporal dynamics. Thus they offer the potential to revisit and advance theories of international relations in general and of international arms trade in particular (Thurner et al. 2019, p. 1737).

Studying arms transactions helps understand overall power shifts in the global political system since weapons are a key component of the "international security" structure (Buzan & Waever 2003, p. 6, p. 216; Harkavy 1994, p. 11; Thurner et al. 2019, p. 1737) The past years' expansion of arms trade and militarisation reflect states' adaptation to the new geopolitical reality. That is, the return of realist politics and economic protectionism at the expense of the US-led post-1945 rules-based international order. Indicators thereof are the retreat of powerful states from multilateral obligations (Eisentraut et al. 2019, p. 6, Munich Security Conference), with intensifying trade wars

(Arriola et al. 2023, p. 6), friendshoring, and nationalisation of strategic industries (Aiyar et al. 2024, p. 1; Wezeman et al. 2024, p.1; Tian et al. 2024, p. 1).

***Research gap.*** This overall destabilisation of the international economic system (Orhan 2022, p. 141) sped up the trend to renationalise the weapons industry. Leaders started emphasising the need to produce military equipment domestically and the importance of cooperation with trusted partners to secure military infrastructure. Given increasing trade diversions, disruption of supply chains (Orhan 2022, p. 141; Aiyar et al. 2024, p. 1), rise in military spending, and the expansion of arms trade, it is fair to suspect relevant shifts in the global weapons distribution network in recent years.

Yet, the shape and factors driving the arms transfer network of the past 5 years have not been systematically investigated. This leaves an important knowledge gap. Furthermore, knowledge about how this network should be contextualised in the post-Cold War era is incomplete. While overall, arms trade activities are embedded in the post-world war order of the past 80 years, the fall of the Berlin Wall reorganised the international political economy to a large extent. Anderton (1995, p. 524) recognised that “[t]he end of the Cold War has increased the relative importance of economic causes and consequences of arms transfers.” Thus transfers during and after the Cold War should be treated as two fundamentally distinct networks (Thurner et al. 2019, p. 1737).

Earlier studies found evidence that after the Cold War, changes occurred in the topology of the arms trade network (i.a. Thurner et al. 2019, p. 1737; Pamp et al. 2021, p. 7), as well as in the relative contribution of security, economic, and normative-cultural determinants on arms trade decisions and arms trade volumes (i.a. Martínez-Zarzoso & Johannsen 2019, p. 2; Thurner et al. 2019, p. 1759). Despite noting these tendencies from descriptive statistics (i.a. Akerman & Seim 2014; Thurner et al. 2019; Lebacher et al. 2020; Lebacher et al. 2021; Fritz et al. 2021; Pamp et al. 2021), the authors of these studies routinely pool arms transfer data from the pre- and post-1990 period in their inferential network models (i.a. Thurner et al. 2019; Lebacher et al. 2020; Fritz et al. 2021; Pamp et al. 2021). This suggests changes in the relative importance of predictors from the Cold War to the post-Cold War period may be overlooked. The most expansive time spans covered in these studies range from the 1950s to the 2010s, meaning ca. two third of the observations are drawn from the Cold War era and one third is made up of post-Cold War years. Therefore, empirical insights produced by these investigations are likely dominated by features of the bipolar Cold War system (Mehrl & Thurner 2025, p. 2) at the expense of the post-Cold War unipolar network.

***Research goal.*** Acknowledging this systemic difference, this study will be the first to model the arms transfer network exclusively for the complete post-cold war period. Joining in other authors’ efforts to establish an arms trade network literature in the past 10 years’, this study pursues four central goals. First, to track the evolution of the international arms transfer network in the post-cold war years (1993–2023). Second, to provide an up-to-date review of the emerging literature on international arms transfer networks. Third, to assess old and new hypotheses about the arms trade network formation process and to draw a working model therefrom. Fourth, to empirically identify the relevant external drivers and internal dependencies that impact states' odds of transferring arms over time. Thus this paper addresses the following research questions:

a) ***Which endogenous dependencies characterise the post-Cold War international arms transfers network?***
b) ***Which exogenous drivers – both on country and relational level – impact the probability of the post-Cold War international arms transfers?***

***Structure.*** To answer these questions, the present study first builds a network time series with six time steps within the 1993-2023 period using the newest round of the SIPRI Arms Transfers Data (SIPRI 2024a). Next, a canon of network descriptive statistics provide insight into the networks' topology. Finally, a sequence of temporal exponential random graph models (TERGM, Handcock et al. 2010) provide estimates of the relative impact of exogenous drivers and endogenous dependencies on arms transfer probability.

## 2. Systematic review of the arms transfer network literature

Prior to network models, the econometric gravity model of trade was the standard framework to analyse weapon transfers. It includes traditional determinants from trade theory related to economic mass and transaction costs. (Feenstra 2016, p. 144-47) However, as Ward, Ahlquist, and Rozenas (2013) point out, the dyadic independence assumption of the gravity model is theoretically and empirically untenable in socio-economic settings (Ward et al. 2013; Thurner et al. 2019, p. 1745). This is especially true for arms transfers which differs substantially from trade in other goods and services. Due to the security implications of arms transfers, manufacturers typically require explicit government permission to export. Thus in this case, it is sensible to consider states instead of firms as central actors. (Ward et al. 2013) Transfers between two states, in turn, change geostrategic calculations of other members of the international system. The dyad's transaction should matter especially to their allies and rivals. (Lebacher 2020, p. 202; Thurner et al. 2019, p. 1745f.)

To account for these endogenous dependencies, a recent strand of literature suggests the use of network models (Pamp et al. 2021, p. 4). The traditional gravity model was extended with network assumptions to capture systemic complexities of arms trade. (Thurner et al. 2019, p. 1739; Lebacher 2020, p. 202f.; Pamp 2021). Since these network statistical methods were not available until recently, empirical network studies of the international arms market only emerged in the past 10 years and remain scarce.

A systemic review is conducted in this paper to assess this young body of literature. First, a list of potentially relevant publications was gathered from the Web of Science and Scopus databases, using the query [ *("arm* transfer*" OR "arm* trade" OR "sipri" OR "weapon* transfer*" OR "weapon* trade") AND ("network" OR "*ergm")* ]. All existing English peer-reviewed articles, conference proceedings, and book chapters published up to 31.08.2024 were retrieved, scanned for duplicates, and titles and abstracts were then manually screened for off-topic results. This review only considers studies of the post-1945 arms transfer networks. To satisfy inclusion criteria, the articles are to study the international arms transfer network 1) using an inferential model, 2) covering a post-WWII period, 3) focusing on major conventional weapons (i.e. excluding small weapons), and 4) focusing on interstate arms trade (i.e. excluding non-state or supra-state actors). After initial cleaning, 14 studies were identified for the review, as presented in table 1.

***Table 1**. Review of the international MCW arms trade literature*

| | **Author (Year)** | **Period** | **Outcome variable** | **Model** |
|---|---|---|---|---|
| **1** | Akerman & Seim (2014) | 1962-2000 | trade presence (binary) | Pooled OLS (linear probability model) with country fixed effects |
| **2** | Kinne (2016) | 1995-2010 | trade presence (binary) | SAOM |
| **3** | Thurner et al. (2019) | 1950-2013 | trade presence (binary) | TERGM |
| **4** | Lebacher et al. (2020) | 1952-2016 | trade volumes (valued) | Network disturbance model |
| **5** | Lebacher et al. (2021) | 1950-2016 | trade formation & trade persistence (binary) | STERGM (inc. country & temporal random effects) |
| **6** | Beardsley et al. (2020) | 1960-1999 | community membership & network hierarchy (binary) | Log. regression; TERGM (inc. additive & multiplicative effects); block modelling |
| **7** | Fritz et al. (2020) | 2016-2017 | trade presence (binary) | STERGM; Relational event model |
| **8** | Fritz et al. (2021) | 1950-2017 | trade presence & repetition of yearly observable sales units (counts) | STERGM & semiparametric count network (inc. country & time varying effects) |
| **9** | Pamp et al. (2021) | 1955-2018 | 2 stages, trade formation (binary) & transfer volume (valued) | Heckman 2-stage selection model with network analysis |
| **10** | Jang & Yang (2023) | 2012-2018 | trade presence (binary) | ERGM |
| **11** | Lee et al. (2023) | 1994-2013 | trade presence (binary) | Semiparametric TERGM |
| **12** | Chou et al. (2023) | 1951-2003 | transfer volume (valued) | OLS |
| **13** | Wang et al. (2023) | 2015-2020 | trade presence (binary) | STERGM |
| **14** | Nicola et al. (2023) | 2018 | trade presence (binary) | ERGM & Additive and Multiplicative Effects Model (AME) |

## 3. A network-political economy model of international arms transfers

International political economy and network theories inform the model of international arms trade of this paper. Contributions from the political economy literature includes a) the arms supply and demand model proposed by Levine, Sen, and Smith (1994), and b) its incorporation into the gravity equation of trade (first defined by Isard 1954; applied to trade by Tinbergen 1962; Linneman 1966; Poyhonen 1963; discussed by Feenstra 2016, p. 133 f.; Ward & Hoff 2007). It is expressed as

$$Y_{ij} = A\frac{M_i M_j}{d_{ij}^{\rho}}$$

Contributions from the network literature includes a) the consideration of network dependencies for the gravity equation of trade by Ward et al. (2013), b) the development of inferential network approaches – especially the T(ERGM) that offers specification of temporal dependencies (Wasserman & Pattison 1996; Hanneke et al. 2010), and c) and its application to the arms transfer network – first undertaken by Thurner et al. (2019, p. 1745). The TERGM enables longitudinal network models by including Markov Chain dependencies for discrete time steps. The function is given by (Hanneke et al. 2010, p. 586-588; Czarna et al. 2016, p. 9; Thurner et al. 2019, p. 1751)

$$P_{\theta,\mathcal{Y}^t}\left(\mathrm{Y^t} = y^t \mid \mathrm{Y^{t-1}}, \dots, \mathrm{Y^{t-k}} = y^{t-k}, n \text{ actors}\right) = \frac{exp\ \{\theta' \mathrm{g}(y^t, y^{t-1}, \dots, y^{t-k}\}}{\sum_{z^t \in \mathcal{Y}^t} \exp\ \{\theta' \mathrm{g}(z^t, z^{t-1}, \dots, z^{t-p})}, \qquad y^t \in \boldsymbol{\mathcal{Y}^t}$$

From these authors' insights, this paper derives an integrated network-political economy model of international arms transfers. The first group of exogenous factors that influence the weapons transfer network are country covariates, i.e. nodal attributes. In the gravity equation (eq. 1), these attributes correspond to the economic "masses" $M_i$ of country $i$ and $M_j$ of country $j$. In the context of arms transfers, these masses may encompass any attribute that makes a country gravitate towards trading activities, including strategic factors. To quantify the push and pull effects in the gravity equation, hypotheses are formulated separately for exporters and importers (Thurner et al. 2019, p. 1738). Both economic and security drivers of arms supply and demand are considered.

The second group of exogenous factors influencing the weapons transfer network are relational covariates, i.e. dyadic attributes. In the jargon of the gravity equation, these relational attributes conceptualize the transaction costs of trade $d_{ij}^{\rho}$ between any two countries $i$ and $j$. In the case of military goods, these transaction costs include the "social, political, and economic distance" between two countries. This distance captures trade barriers, preferences, and capabilities of the dyads (Feenstra 2016, p. 133, 168; in Thurner et al. 2019, p. 1738 ff.) Trade barriers include for instance tariffs, quotas, agreements, embargos, and other border effects (Pamp et al. 2021, p.1f.; Wang et al. 2023, p.3f.; Lebacher 2020, p. 202f.; Thurner et al. 2019, p. 1738, 1745, 1749). When and how these barriers are imposed is informed by political and strategic interests. Arms sales are one of the most potent foreign policy tool in the arsenal of major powers. They use it to strengthen their allies' defences, influence domestic policies of their client states, balance against their rival's influence, or impose outright hegemony on the importer (Spindel 2023). Therefore, when trading strategically important goods such as weapons, economic and political compatibility both play a major role.

The mechanisms outlined above come together to create structural effects, observable as endogenous attributes proper to the network. In the international arms trade network, these are expected to be low out- and indegree, low trade reciprocity, high nested transitivity, high path dependency, and linear expansion (Thurner et al. 2019, p. 1746). Table 2 presents hypotheses derived from the supply- demand model of trade and the TERGM, applied to the case of international arms transfer network.

***Table 2**. Hypotheses*

| **Country (node) covariates** |
|---|
| Hypothesis 1 (market size) |
| 1a) The larger a state's market size, the higher its likelihood of arms export.<br>1b) The larger a state's market size, the higher its likelihood of arms import. |
| Hypothesis 2 (arms supply and demand capacity) |
| 2a) The larger a state's military spending, the higher its likelihood of arms export.<br>2b) The larger a state's military spending, the higher its likelihood of arms import. |
| Hypothesis 3 (population size) |
| The larger the state's population, the higher its likelihood of arms import. |
| Hypotheses 4 (internal instability) |
| 4a) A state with a coup is more likely to import arms than one without a coup.<br>4b) A state in internal armed conflict is more likely to import arms than without.<br>4c) A state in internal armed conflict is less likely to export arms than without. |
| Hypothesis 5 (external instability) |
| 5a) A state with high sovereignty is less likely to import arms than a state with low sovereignty.<br>5b) A state in external armed conflict is less likely to export arms than without.<br>5c) A state in external armed conflict is more likely to import arms than without. |
| Hypothesis 6 (dimensions of armed conflict) |
| 6a) A state in armed conflict due to territorial issues is less likely to export and more likely to import arms than without such conflict.<br>6b) A state in armed conflict due to government issues is less likely to export and more likely to import arms than without such conflict.<br>6c) A state in a high intensity conflict (i.e. minimum 1000 casualties) is less likely to export and more likely to import arms than without such conflict.<br>6d) A state in a low intensity conflict (i.e. < 1000 casualties) is less likely to export and more likely to import arms than without such conflict. |

| |
|---|
| **Relational (dyad covariates)** |
| <u>Hypothesis 7 (economic homophily)</u> |
| Two countries belonging to the same market size class are more likely to trade arms with one another than if they were not in the same market size class.<br>- GDP lower 25%<br>- GDP middle 50%<br>- GDP upper 25% |
| <u>Hypothesis 8 (political homophily)</u> |
| The more different the political regimes of two countries, the lower the likelihood of them trading arms. |
| <u>Hypothesis 9 (alliance & conflict relation)</u> |
| 9a) Two allies are more likely to trade arms than two non-allied countries.<br>9b) Two adversaries in armed conflict are less likely to trade arms than two non-adversaries. |
| <u>Hypothesis 10 (geographic distance)</u> |
| The greater the geographic distance between two countries, the lower the probability of them trading arms. |
| **Cross-sectional network dependencies** |
| <u>Hypothesis 11 (market concentration)</u> |
| 11a) Countries are less likely to export arms than statistically expected.<br>11b) Countries are less likely to import arms than statistically expected.<br>11c) Countries are less likely to reciprocate arms transfers than statistically expected. |
| <u>Hypothesis 12 (hierarchical clustering)</u> |
| Two countries connected by arms trade are more likely to share a common trade partner than statistically expected, with this effect weakening as the number of additional shared partners increases. |
| **Temporal network dependencies** |
| <u>Hypothesis 13 (path dependency – resistance to formation of new trade ties)</u> |
| The likelihood for new arms trade relations to emerge over time between previously unconnected countries is lower than statistically expected. |
| <u>Hypothesis 14 (linear growth)</u> |
| The arms trade network expands linearly over time more than statistically expected. |

## 4. Data & Method

***Dyadic data.*** Dyadic datasets on arms transfers, alliances, armed conflicts, and geographic distance were retrieved from different sources. The most comprehensive record of international weapons trade is the SIPRI Arms Transfers Database provided by the Stockholm International Peace Research Institute (SIPRI). The most recent round (updated 13th March 2024) was retrieved (SIPRI 2024a). Data on interstate alliance relations come from the Alliance Treaty Obligations and Provisions (ATOP) covering 1815-2018 (v5.1) (ATOP 2022; Leeds 2022; Leeds et al. 2002). ATOP records dyad-year information on the number of bilateral and multilateral military alliance agreements in effect between two states in a given year between 1815 and 2018, including non-aggression pacts. Since the data is already coded in a dyad-year format, no changes to the data was necessary. (ATOP 2022; Leeds 2022) Data on interstate conflicts come from the UCDP Dyadic Armed Conflict Dataset (v24.1) 1946-2023 published by the Upsala Conflict Data Program (UCDP 2024; Davies et al. 2024; Harbom et al. 2008; Pettersson 2024). Capital distance data was calculated from scratch using the latitude and longitude coordinates from the World Cities dataset provided by the Environmental Systems Research Institute (ESRI, 2023).

Upon acquisition, the raw data was cleaned and, where necessary, aggregated to a longitudinal yearly observation format. Where necessary, the dyadic data was converted to a dyad-year format using several different operations. Dyad-year observations are aggregated by time period and missing nodes and missing edges are added and imputed with a zero value to indicate non-occurrence of arms transfer, alliance, or interstate conflict relations. The final output are time series of sociomatrices with harmonised dimensions. Dyadic data on geographic distance was exempted from the aggregation process, as its values remain constant over time, i.e. geographic distance does not vary by year. After this, duplicate entries were examined and either deleted or recoded where necessary. Finally, the dyad-year data set were converted into dyadic matrices needed for network modelling.

***Country data.*** Country datasets were also converted to a country-year format using several different operations, where necessary. The size of a country's arms industry, i.e. the production capacity and demand of military goods, is approximated by its military expenditure. Data on yearly government spending on military goods, services, R&D, and personnel is retrieved from the SIPRI Military Expenditure Database 1949–2023 (SIPRI 2024c). The unit of analysis is USD millions ($10^6$) at constant 2021 prices and exchange rates (SIPRI 2024d). Data on yearly gross domestic product (GDP) and population counts was extracted from the World Economic Outlook data set (version October 2023) published bi-annually by the International Monetary Fund (IMF 2023). The Varieties of Democracy (V-Dem) database (v14.0, Coppedge et al. 2024) provides information on political regime score, coup experience, and the sovereignty score measured in terms of the government's political independence from foreign states (markers of states' internal political stability). Missing country-year entries were first added to the data frame and then imputed by linear interpolation. Country-year observations are then aggregated to country-period level.

***Observations $n$ & $m$.*** The observation period is from 1993-2023 and only UN countries were sampled. Out of the 193 UN member states initially considered, 36 are excluded due to insufficient data profile. The final sample consists of 157 countries. After all preparations, we obtain three time series, each consisting of 6 valued sociomatrices representing the 6 time spells t1-t6. The three series of matrices contain information on interstate arms transfer, alliances, and conflicts among the 157 network members. The arms transfer matrices are directed, while the alliance, conflict, and geographic distance matrices are undirected. In the directed arms transfer matrices, the maximum number of possible ties per matrix is $n(n-1)$ = 157 x 156 = 24492 per time spell. Taken together, the total number of possible arms transfer ties for all six time spells t1-t6 is then 157 x 156 x 6 = 146952 observations. For the undirected alliance, conflict, and distance matrices, the maximum number of edges is $m = n(n-1)/2$ = 157 x 156/ 2 = 12246 per matrix. Across the six time steps t1-t6, the total number of possible alliance and conflicts ties is 12246 x 6 = 73476 observations, respectively. Interstate geographic distance data (in km), a constant over time, is stored in a single matrix of dimension 157 x 157 containing 12246 edges. (Newman 2010, p. 134)

***Edge weight.*** The TERGMs estimated in this paper investigate the occurrence of arms transfer (the extensive margin) rather than the volume of arms transfer (the intensive margin) as the dependent outcome. Thus, binary versions of the three series of matrices are created as inputs for the inferential network models, while the three sets of valued matrices are retained for descriptive analysis (e.g. development of arms transfer volumes over time). Following previous authors (e.g. Akerman & Seim 2014; Thurner et al. 2019), binary cell entries are coded as 1 if two countries have an arms transaction worth at least 0.5 million TIVs in a given time spell, and 0 otherwise. The binary arms transfer ties indicate either the presence (=1) or absence (=0) of trade, whereas weighted ties measure the arms trade volume in million(s) TIVs. As there is little variance in the dyadic alliance and conflict data, their matrices are also dichotomised. In the alliance matrices, value 1 is assigned if two countries share an active alliance or non-aggression agreement in a given time spell, and 0 otherwise. In the conflict matrices, value 1 is assigned if two countries were in armed conflict in a given time spell, and 0 otherwise.

***Estimator.*** The TERGM sequence is estimated using the Maximum Pseudolikelihood Estimator ([MPLE]; Besag 1975 in Robins et al. 2007, p. 186-187; Strauss & Ikeda 1990 in Robins et al. 2007, p. 186-187) with bootstrap corrected confidence intervals implemented in the *btergm()* function from the `btergm` package (Leifeld et al. 2018a, p. 7-8; Desmarais & Cranmer 2012). This estimator functions very well with large networks and is computationally economical, even with complex specifications (Robins et al. 2007, p.187). Therefore, it is chosen to estimate the TERGMs for the arms transfer networks series which is a large network (157 x 157 nodes over 6 time steps). A replication of only 50 bootstrap sample retrievals was carried out considering this study's limited resources.

# 5. Results

## 5.1. Network description

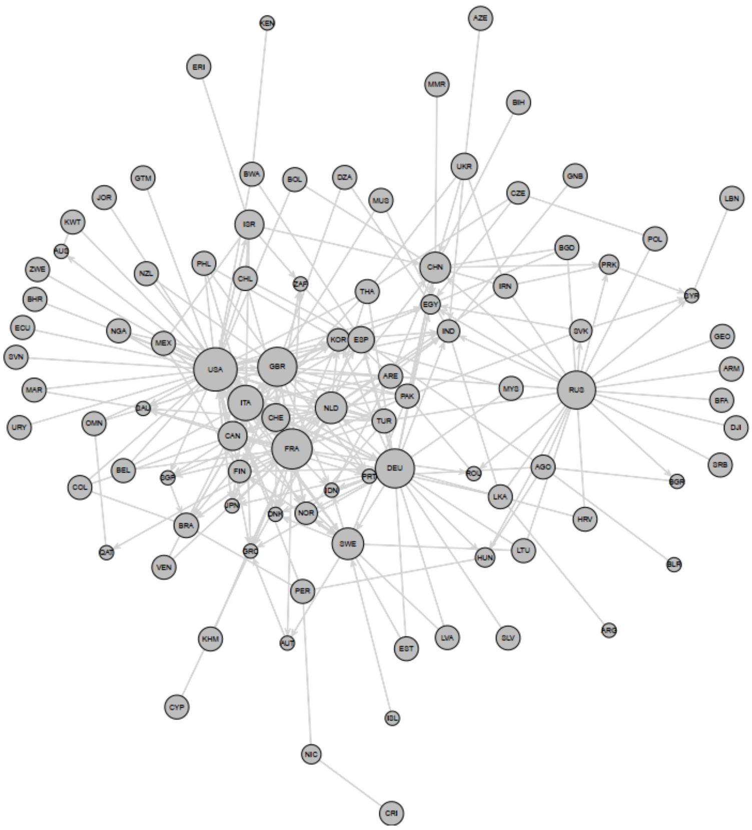
### *5.1.1. Network plots*

Figure 1 (p. 13) visualises the networks of 1993 and 2023. Vertices are scaled by logarithmic outdegree and labelled by ISO 3166-1 Alpha-3 codes. The network has become denser and the number of trade participants grew over time. In 1993, the network is sparser, with key trade hubs centering around the United States (USA), Russia (RUS), the United Kingdom (GBR), Italy (ITA), and Germany (DEU). While their importance persists overtime, by 2023, other major exporters joined the picture, such as China (CHN), Israel (ISR), Sweden (SWD), Spain (ESP), Canada (CAN), or Turkey (TUR). The overall outdegree distribution seems to have become less hierarchical as time passes. This is concluded from the increase in similarly sized nodes, indicating that the playing field has increasingly levelled out over the past 31 years with the emergence of new export stars.

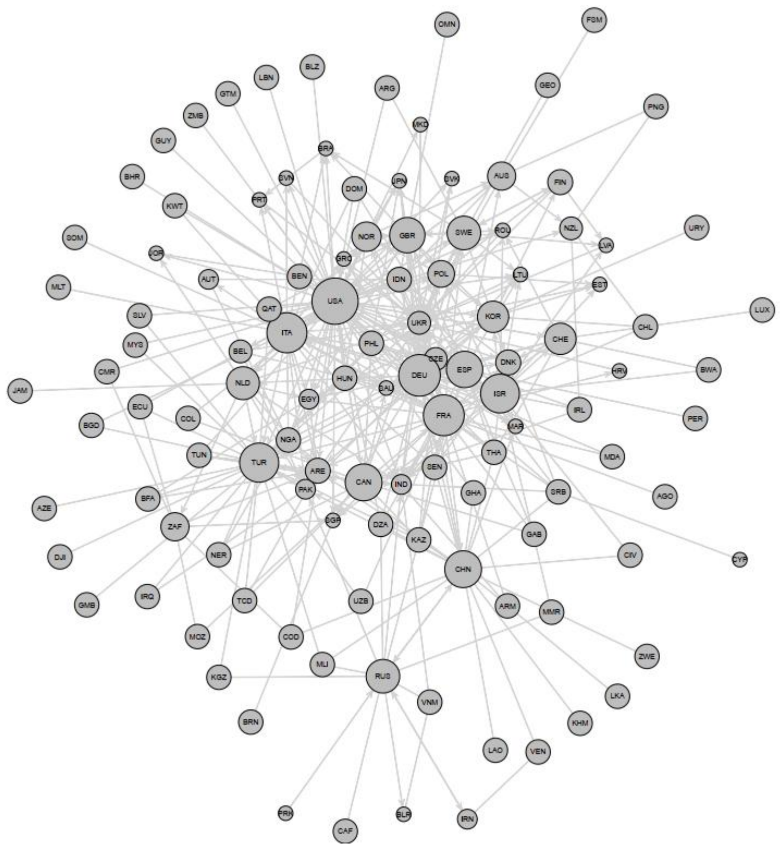
However, this is merely a visual impression that may not hold against formal statistics. The logarithmic scaling factor which regulates the spread of outdegree values is chosen to be small. A smaller scaling factor decreases the likelihood of overlapping vertices, thus ensuring that most vertices are visible in the plot. However, the downside is that the smaller this factor, the stronger the log-scaled outdegree distribution is compressed. A strong compressions makes it  harder to visually spot country differences between smaller and larger outdegree values from visual inspection alone.

***Figure 1.*** *International arms transfer networks: 1993 & 2023*

**1993**




**2023**



#### 5.1.2. Topological properties

Table 3  presents global graph statistics to describe the network topology more accurately.

***Table 3.*** *Global graph statistics - international arms transfer network (1993-2023)*

| Time spell | Edges | Isolates | Components[3] | Density | Reciprocity | Transitivity | Diameter | Av. Path Length |
|---|---|---|---|---|---|---|---|---|
| **t1: 1993-1997** | 629 | 23 | 130 | 0.026 | 0.099 | 0.391 | 376.54 | 40.96 |
| **t2: 1998-2002** | 679 | 27 | 134 | 0.028 | 0.077 | 0.438 | 163.24 | 19.96 |
| **t3: 2003-2007** | 705 | 20 | 125 | 0.029 | 0.105 | 0.381 | 261.80 | 43.04 |
| **t4: 2008-2012** | 820 | 14 | 131 | 0.033 | 0.095 | 0.397 | 236.00 | 25.91 |
| **t5: 2013-2017** | 915 | 15 | 116 | 0.037 | 0.098 | 0.404 | 312.39 | 32.38 |
| **t6: 2018-2023** | 953 | 8 | 108 | 0.039 | 0.101 | 0.385 | 219.49 | 39.51 |

[1] N = 157 across the 6 networks
[2] Data source: SIPRI Arms Transfers Database (2023)
[3] Reference to strong components

***Edges, isolates, components,*** During the observation period 1993-2023, the number of arms trade ties *m* (edges) increased consistently from 629 in t1 to 953 in t6, while the number of states *n* (nodes) considered in the arms trade network is kept at 157. Overall, arms trade activities grew as countries become more connected, also recognisable from the continuous decrease of isolates from 23 in t1 to 27 in t2, and then to 8 in t6. The number of strong components ranges between 108 and 134, but there seems to be no clear up- or downwards trend until period t4 (1993 – 2012). Starting from period t5, the amount of components dropped sharply from 131 to 116, signalling a sudden increase in network connectivity.

***Density.*** All of this points to a post-Cold War network growth which is also reflected in the networks' growing density, a statistic measuring the overall connectedness among vertices in a graph (Scott 2017, p. 69). It describes the number of actually existing links relative to the maximum possible number of ties. (Newman 2010, p. 134) Applied to our arms transfer network, a value 1 indicates that every country trades with all the other countries in the network, while 0 means that no weapons are traded at all. As seen in table 2, density of the arms trade networks ranges from 0.026 - 0.039 between the t1 and t6 periods. In t1 (1993-1997), 2.6% of all possible trade links are present. Over time, the network density grew until it peaked at 3.9% in t6 (2018-2023). So on average, there is a probability of between 2.6% and 3.9 % that any two countries *i* and *j* trade arms. The network became denser and more populated over time. Yet despite this expansion, it is very sparse compared to other trade networks. The density of the overall aggregated world trade grew from 74 % in 1995 to 85% in 2014 (Cepeda-López et al. 2019, p. 18). This confirms the theoretical intuitions that states are more selective about their arms trade partners compared to trades in "civil" goods.

***Path length, geodesic, diameter.*** The *path length* is the number of links separating two nodes along a path way. Out of all possible paths linking two vertices, the shortest is called *geodesic*. It is the minimum number of edges a node must traverse to reach another. (Newman 2010, p. 139) In the arms trade network, it describes the lowest number of intermediary states an arms delivery must pass through to change hands between the initial sender and end final receiver. When comparing all geodesics in the network, the most extended geodesic found in the whole network determines the *diameter*. In other words, the network diameter is the longest shortest path possible connecting two vertices. (Newman 2010, p. 140) Looking at the six arms trade networks, we see that the diameter evolves erratically in the post-Cold War era. It declined sharply from ca. 377 edges in the t1 network to ca. 163 edges in the t2 network, before climbing up to ca. 262 edges in t3, and then declines, rises, and declines yet again from t4 to t6.

Finally, averaging the geodesics of all dyads in the network yields the *average path length*, denoted as L. It gives the average shortest distance connecting two nodes in a network and is a marker for trade efficiency (Newman 2010, p. 560). Watts & Strogatz (1998, p. 442) generalised this idea as the small-world effect, whereby "short cuts" facilitate circulation of resources in a network (Watts & Strogatz 1998, p. 442). Shorter average path lengths in the arms trade system indicates higher network traffic and connectivity, with speedy arms transfers along an uncomplicated delivery chain, which reduces transaction costs. (Jiang et al. 2021, p. 4-5) In the arms transfer network, the average path length statistic does not evolve in linear fashion over time. It ranges between ca. 20 and 43 steps, starting off with ca. 41 in t1 then declining to ca. 20 in t2, before continuing to rise and decline alternatingly during the remaining observation period. The highest value is found in t3 (2003-2007), where on average, military goods have to be passed through 43 intermediary states before reaching the receiver country. The lowest value is found in t2 (1998-2002), where it takes on average 20 steps to connect two countries along the shortest weapons transfer path.

***Reciprocity.*** The statistic *reciprocity* measures the "frequency of occurrence of these loops […] of length two", telling us "how likely it is that a vertex that you point to also points back at you" (Newman 2010, p. 204). New trade theory suggests that reciprocity is a marker for intra-sectional trade, which is a pervasive feature of international trade especially since the acceleration of globalisation from the 1980s onwards (Melitz 2003, p. 1695; Krugman 1979; Krugman 1980). However, compared to other trade networks, reciprocity is low for weapons trade. Between 1993-2023, the fraction of edges being reciprocated is between 0.077 to 0.105, meaning 7.7 to 10.5 percent of the existing arms transfers are reciprocated. Reciprocity remains constant over time, circling around the 10% value apart from a dip in t2 at 7.7%.

***Transitivity.*** Transitivity, also called triadic closure, describes a phenomenon whereby two connected nodes *i* and *j* share a connection with a third node *k*. In the international arms transfer context, transitivity describes a situation where, if country a trades arms with country b, and country b trades arms with country c, then countries a and c also trade arms Transitivity is quantified by the clustering coefficient $C$ (Holland & Leinhardt 1970; 1971) which "measures the average probability that two neighbors of a vertex are themselves neighbors." (Newman 2010, p. 449). Its value ranges from 0 (no closed triads in the network) and 1 (perfect transitivity) (Newman 2010, p. 199). In the arms transfer network, transitivity remains stable over time, with values ranging between ca. 0.38 and 0.44 from 1993 to 2023, meaning there was a 38% to 44% probability that two countries with a common trade partner also trade with each other. This reflects the "a friend of a friend is also my friend" idea. This trend may come from the countries' desire to pool risks (Bramoullé et al. 2019 in Lebacher et al. 2021, p. 211) or to trade with tried and tested partners that are known to a common "friend". This mechanism is especially relevant when goods with security implications are traded. The clustering coefficients of 0.4 in the arms transfer network is very high – a trait found in most social networks. It is about 100 times bigger than a coefficient we would expect if the arms trade relations were formed at random. (Newman 2010, p. 237, p. 262).

### *5.1.3. Centrality measures*

The centrality statistics answer the question of "Which are the most important or central vertices in a network?" (Newman 2010, p. 168) More than one definition exists for node importance, and by extension, more than one centrality measure exists. (Newman 2010, p. 168 f.) In the international political economy of weapons trade, a country's influence or centrality can be translated into its ability to 1) attract a high number of importers and/or exporters (indegree and/or outdegree centrality), 2) create ties with well-connected and influential trade partners (eigenvector centrality), 3) pass on weapons or negotiate terms between unconnected states in the supply chain (betweenness centrality), or 4) reach out to trade partners easily to obtain or distribute arms efficiently and quickly (closeness centrality). (De Benedictis et al. 2013; Herman 2022, p. 131). Table 4 (p. 17) presents these statistics for the international arms transfer network between 1993-2023 in 6 time steps t1-t6.

***Table 4.*** *Centrality statistics - international arms transfer network (1993-2023)*

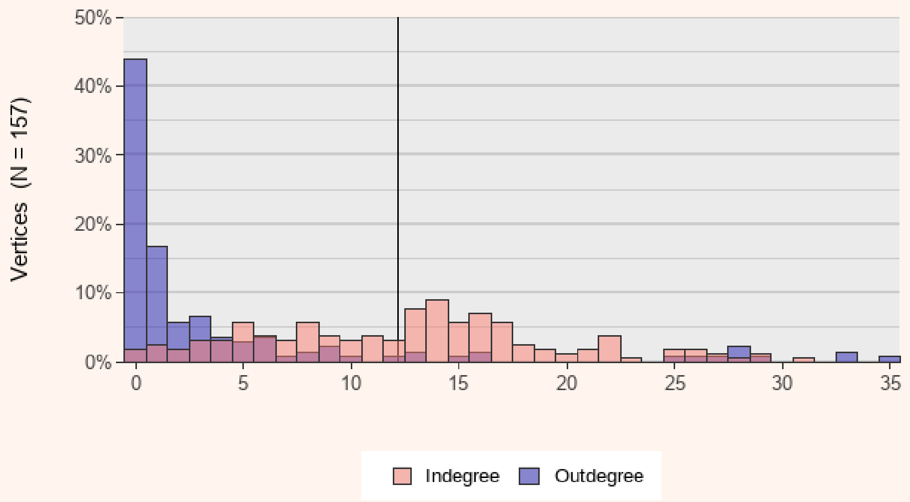
| Measure | Mean | SD | Median | Range | IQR | Skew |
|---|---|---|---|---|---|---|
| Indegree | 12.675 | 6.956 | 13.000 | 31 (0-31) | 10.000 | 0.311 |
| Outdegree | 12.675 | 25.113 | 1.000 | 124 (0-124) | 9.000 | 2.488 |
| Betweenness | 113.287 | 329.639 | 5.689 | 3106.53 (0-3106.53) | 71.858 | 6.172 |
| Closeness | 0.070 | 0.230 | 0.002 | 1 (0-1) | 0.004 | 3.542 |
| Eigenvector | 0.032 | 0.073 | 0.000 | 0.31 (0-0.31) | 0.020 | 2.696 |

***Degree centrality.*** Degree centrality which sums up all edges directly connecting node *i* to another node *j* (Newman 2010, p. 133, eq. 6.19; Nieminen 1979 in Scott 2017, p. 96). In a directed network, the in-degree is the sum of a node's incoming ties, while the out-degree is the sum of a node's outgoing ties (Newman 2010, p. 135, eq. 6.25; Knoke & Burt 1983 in Scott 2017, p. 97). Averaging over all network members' in- and outdegrees, we get the graph level mean in-degree $c_{in}$ and mean out-degree $c_{out}$ (Newman 2010, p. 135, eq. 6.27). Both are identical since the number of sent edges should equal the number of received edges (Newman 2010, p. 135). In the arms trade network, the outdegree of node $i$ is interpreted as the number of countries it exports to, and indegree is the number of countries it imports from. Table 5 informs us that the arms transfer mean indegree and mean outdegree of the 157 countries is $\mu$ = 12.68. This means that on average, the network members sell to and buy from 13 arms trade partners during the observation period 1993-2023.

Dispersion measures are generally larger for the outdegree than for the indegree distribution, meaning outdegrees are more hierarchically distributed in the network than indegrees. Arms transfer outdegree values range from 0 to 124, meaning there are countries that do not export any at all and at least one that exports to as many as 124 other countries. The outdegree median value 1 indicates that the lower 50% of countries either do not export at all or if they do, they only export to one country. This is likely because most countries are not able or willing to produce their own weapons. The indegree values range between 0-31, meaning there are countries that do not import weapons and at least one country that source its weapons from 31 different providers. The median of 13 indicates that about 50% of countries import their weapons from maximum 13 trade partners and the rest from more than 13 partners.

Figure 2 visually contrasts the relative in- and outdegree distributions for the 157 countries pooled over the 1993-2023 period. The pink histogram shows indegree and the blue histogram shows the outdegree distribution. The y-axis shows the percentage of network members that have the specific in- or outdegree.

***Figure 2**. In- and outdegree distributions 1993-2023 pooled (relative frequency)*

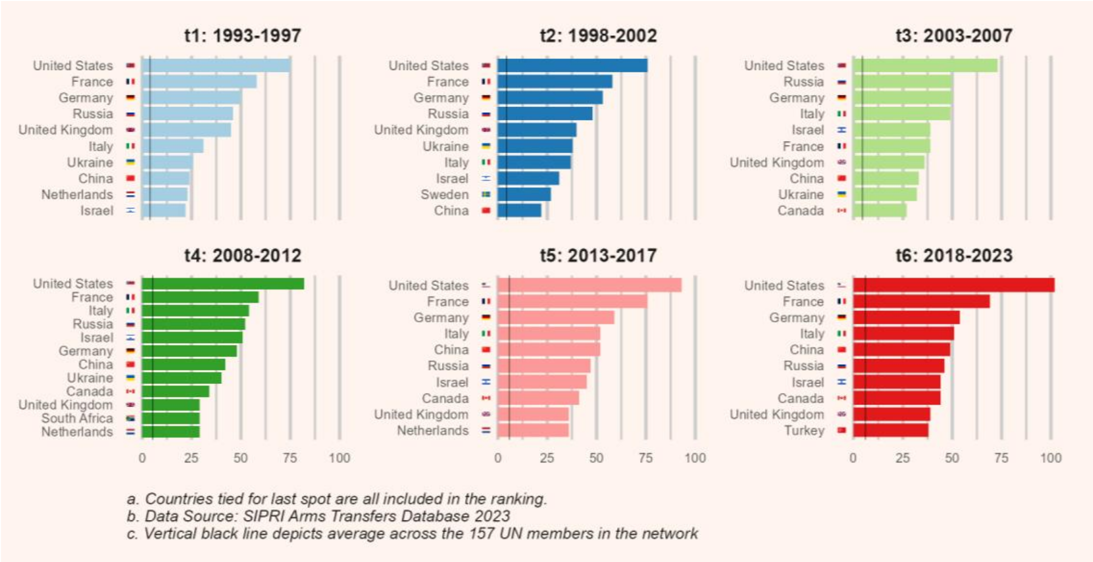



Notes:
a. Vertical black line depicts the average degree among the 157 UN members.
b. Indegree: range = 0-31, median = 13.
c. Outdegree: range = 0-124, median = 1.
d. Degree value on x-axis cut off at 35.
e. Data Source: SIPRI Arms Transfers Database 2023.

The indegree distribution (pink) of arms transfers is very homogeneous, with values clustering around the range 13-17. The number of countries that do not import military equipment at all during the 1993-2023 period is at ca. 2%, while ca. 17% of countries import from ca. 13-14 suppliers. On the other hand, the outdegree distribution (blue) is highly heterogeneous with an extreme right skew. The bulk of countries have an outdegree value of 0 or 1. More than 40% of the 157 network members have an outdegree of 0, meaning they do not export arms, and over 15% export to only one other country. A tiny number of countries are strong exporters with a huge customer base. This is a pattern called "preferential attachment" (Barabási & Albert 1999). In the arms transfer context it means there is a tendency for network members to import preferably from a selected few, either because these providers are very popular and/or because they are the only providers available on the market in the first place.

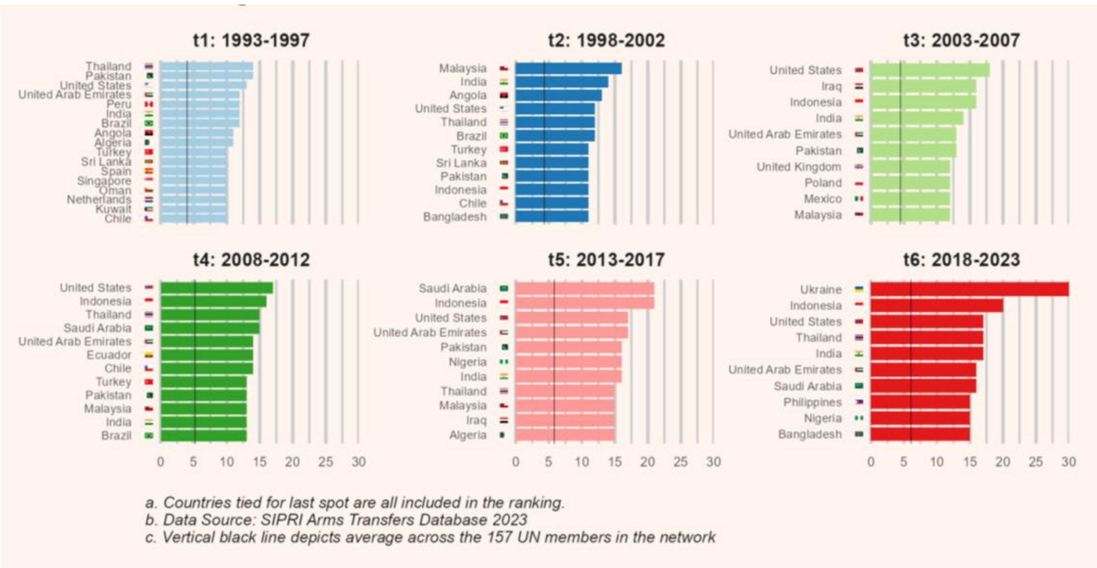
As depicted in figure 3 (p. 19), the top exporting country terms of outdegree centrality is the United States at all time spells, followed most often by Germany, France, Russia, the United Kingdom, Israel, Italy, and China. As for the top importers, figure 4 (p.18) shows that the United States also belongs to the top 5 in terms of indegree centrality at all time spells, followed by Indonesia, Thailand, and United Arab Emirates with four appearances, India with three, and Pakistan at two time spells.

***Figure 3***. *Top 10 outdegree (export ties) by time period*




***Eigenvector centrality.*** Eigenvector centrality (Bonacich 1987) is a refined version of degree centrality and evaluates a node's network influence not only based on the quantity, but also on the quality of its connections. Given two nodes with the same number of connections – the one is considered more influential whose connections themselves have a higher degree score in total (Newman 2010, p. 170). While degree centrality only captures how well connected a country is on the international arms market, eigenvector centrality also captures how well connected that country's trade partners are (Herman 2022, p. 131). Eigenvector centrality is indicative of social capital which Lin (2001, p. 12) – drawing on Bourdieu (1986) – defines as "resources embedded in a social structure which are accessed and/or mobilized in purposive actions". A state's social capital regarding arms trade consists of its ties to influential others in the system.

***Figure 4***. *Top 10 indegree (import ties) by time period*




Between 1993-2023, the period-averaged distribution ranges between 0 and 0.31 eigenvector centrality scores, with a mean value of 0.032 points. The distribution has a large variation, with a standard deviation (SD) σ of 0.073 points which is more than the double the value of the mean eigenvector centrality. The interquartile range (IQR) of 0.02 tells us that the middle 50% of countries have a variation of 0.02 eigenvector centrality points. The positive and large skew measure (= 2.7) points to a right tail distribution. The top ranking countries in terms of their social capital, measured by eigenvector centrality, are Germany and the United States occupy most of the time, followed by France, Sweden, United Kingdom, Israel, and Italy.

***Betweenness centrality.*** Betweenness centrality captures a state's influence as a mediator of trade relations. (Anthonisse 1971 in Freeman 2004; Freeman 1977 in Newman 2010, p. 185). This statistic "measures the extent to which a vertex lies on paths between other vertices" (Newman 2010, p. 185) and is calculated by counting how often other vertices, while travelling on their shortest paths, need to pass by node $i$ to reach the remaining network members. (Newman 2010, p. 187)

Betweenness centrality is linked to Granovetter's (1973, p. 1361) "tie strength" concept which measures the amount of resources that go into establishing a tie. Strong ties refer to edges situated in dense clusters with many interrelated, redundant relations, while weak ties refer to edges situated in sparse areas of the graph. The weakest tie is the "bridge", defined as the only link existing between two vertices (Harary et al. 1965, p. 198 in Granovetter 1973, p. 1364). Burt (1992) suggests that nodes acting as "bridges" have a special type of power by being the only ones that close "structural holes" (Burt 1992) between otherwise unrelated network components. The ability to bridge structural rifts provides two benefits. First, brokers are the only actors privy to all opportunities that are offered by the unconnected actors. Second, brokers can control which and how many resources are passed along the bridge they create. (Burt 1992, p. 32; Burt 2004, p. 351).

In the arms transfer network, betweenness centrality is a proxy for states' importance as "bridges", that is, as a distributor in the arms supply chain. It quantifies how much a node is needed to close gaps so that market members can interact. That is, how much arms traffic in the network would be disrupted if the node were to be removed? Higher betweenness centrality gives the ability to control market participation and weapon flows (Newman 2010, p. 185). For the arms transfer network, betweenness centrality ranges between 0 and 3107. On average, the 157 network members have a betweenness centrality of 113 points, meaning most countries have 113 instances of passing on weapons between two countries on the shortest trade route that connects them. The top 10 countries in terms of their betweenness centrality act as important arteries of trade activities in the network. As with the other centrality measures, the United States tops the charts, apart from t6, when it was overtaken by Ukraine. France, the United Kingdom, Russia, and China feature often, but otherwise there is no clear pattern in the ranking. Countries entering the top 10 change frequently.

***Closeness centrality.*** Closeness centrality informs us how far a vertex is from the remaining network members by counting the minimum number of edges the vertex has to travel to reach each of the other vertices. (Newman 2010, p. 182) Being close to as many network members as possible is important for quickly accessing or distributing resources, such as critical goods or information. In the arms trade network, closeness centrality quantifies how well a country is "directly connected […] to the rest of the world" (De Benedictis et al. 2013; Herman 2022, p. 131). Higher scores indicate the ability to contact arms producing and purchasing countries more directly. This translates into the ability to obtain or provide weapons with little effort, as quickly and involving as few intermediary countries as possible. For a country in need of seller or customer, weapons trade becomes more straightforward and uncomplicated, with few brokers separating it from other market participants. Closeness to exporters allows quick access to weapons, while closeness to importers improves the ability to sell off stocks.

Because the international arms market is a relatively big network, the closeness centrality takes extremely small values with narrow variances. Most countries are similarly close to the remaining network members. As the network grows over the 6 time spells, the closeness centrality distribution becomes more homogenous, the ranking among countries less hierarchical. The mean is at 0.07 with a large standard deviation of 0.23, resulting in a small standard error of 0.018 points. The skew is 3.54, and combined with a median of 0.002 – which is 35 times smaller than the mean – point to a strong right skewed distribution. There is no clarity and consistency in the top 15 ranking for closeness centrality, as those included in the top 15 change frequently. Vietnam is the closest to being a high ranker, as it occupied the first spot at two time periods, t3 and t6. Other countries that frequently occur in the top 5 are Oman, Malaysia, and Japan.

## 5.2. Model estimates

Figure 5 (p. 23) summarises results from the TERGM estimated for the international arms transfer network 1993-2023 .

### *5.2.1. Endogenous dependencies*

***Density (edges).*** Controlling for endogenous structures, dyadic covariates, and country covariates, model M5 estimates that arms transfers are on average 2.66 times significantly less likely to occur than expected at random (OR = 0.38 [0.23; 0.60] ; logit θ = -0.98 [-1.46; -0.52]). This low density cannot be explained by chance, hence it is considered a dominant trait of the arms transfer network.

***Transitive closure (gwesp).*** Model M5 estimates that two countries with at least one shared arms transfer partner are 1.1 times (by 10%) more likely to be in an arms transfer relationship, all else in the model remaining equal (OR = 1.10 [1.06; 1.16] ; logit θ = 0.01 [0.06; 0.15]). This supports hypothesis 12 that two countries trading arms are more likely to also share one (or several) trade partner(s) than statistically expected, with this effect weakening as the number of additional common partners increases. It seems the 'a friend of my friend is my friend' phenomenon strongly structures the arms transfer network, leading to clusters of trade activities.

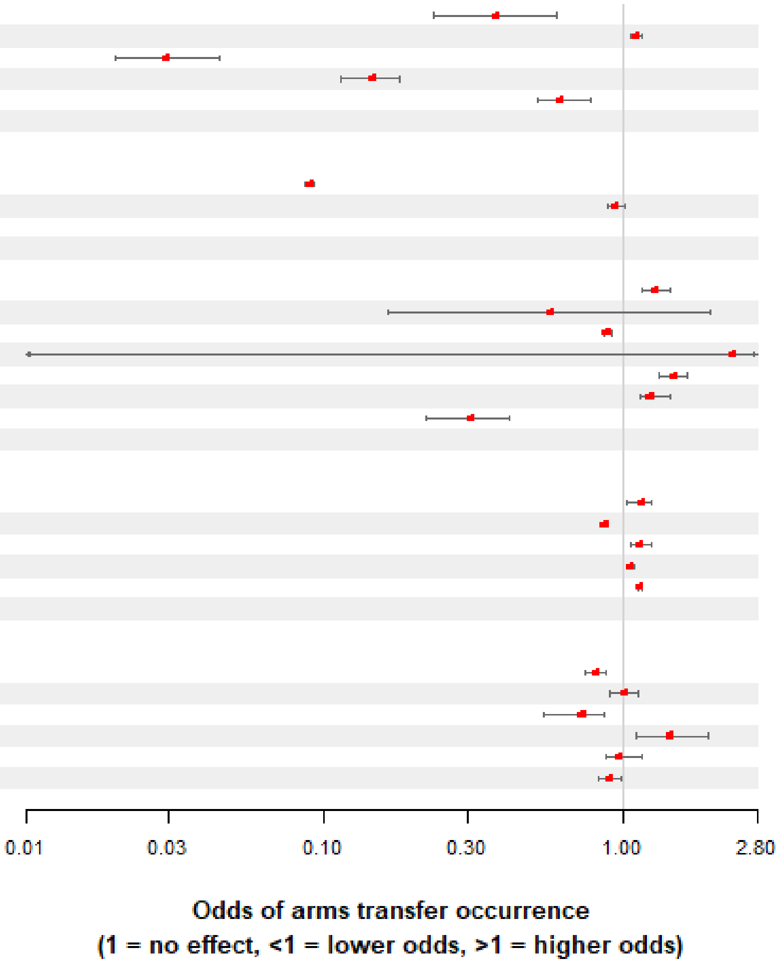
***Arms export and import (gw-outdegree and gw-indegree).*** Model M5 estimates the odds of a country exporting arms is on average ca. 33.9 times lower than chance would allow, all else held constant. This means there are very few net exporters (OR = 0.03 [0.02; 0.04] ; logit θ = -3.52 [-3.91; -3.11]), with the probability of arms exports decreasing further as a state's outdegrees increases. Model M5 also estimates that the odds of a country importing arms is on average ca. 6.9 times lower than statistically expected (OR = 0.15 [0.11; 0.18] ; logit θ = -1.93 [-2.17; -1.73]). This probability decreases even further with each additional supplier a state acquires. Thus hypotheses 11a) and 11b) relating to market concentration are supported: countries are indeed less likely to both export and to import arms than statistically expected. A few countries monopolise the international arms market, with the remaining countries being highly dependent on them. This imperfect market constellation points to a pattern of preferential attachment. Most countries only rely on a small number of arms supplying countries, and usually decide to stick to the provider they initially bought from.

***Reciprocal trade***. Model M5 estimates that on average, reciprocal arms transfer is 1.6 times (60%) less likely to occur than statistically suggested, conditional on the rest of the network (OR = 0.62 [0.52; 0.77] ; logit θ = -0.48 [-0.66; -0.26]). This supports hypothesis 11c that arms transfer flows tend to be one-directional.

***Linear trade expansion over time***. As the estimate for linear network growth is very small and includes the null hypothesis value in their confidence intervals (OR = 0.94 [0.89; 1.01]; logit θ = -0.062 [-0.12; 0.01]), it is likely a product of randomness. Therefore hypothesis 14 that arms transfer ties grow linearly over time is rejected in favour of the null hypothesis that there is no linear trend, neither growth nor decline.

***Figure 5**. Forest Plot Model 5 (odds ratios inc. 95% confidence interval)*

| | OR inc. 95% CI, (-1/OR) |
|---|---|
| **NETWORK EFFECTS** | |
| Density (edges) | 0.38 [ 0.23 ; 0.60 ] * ( -2.66 ) |
| Nested transitivity (GW-ESP) | 1.10 [ 1.06 ; 1.16 ] * |
| Exporter effect (GW-outdegree) | 0.03 [ 0.02 ; 0.04 ] * ( -33.87 ) |
| Importer effect (GW-indegree) | 0.15 [ 0.11 ; 0.18 ] * ( -6.89 ) |
| Mutual trade | 0.62 [ 0.52 ; 0.77 ] * ( -1.61 ) |
| **TIME DEPENDENCIES** | |
| New arms trade tie, tendency over t | 0.09 [ 0.09 ; 0.09 ] * ( -11.12 ) |
| Arms trade tie, linear growth over t | 0.94 [ 0.89 ; 1.01 ] ( -1.06 ) |
| **DYADIC EFFECTS** | |
| Relation: allied (1 = yes) | 1.28 [ 1.15 ; 1.44 ] * |
| Relation: armed conflict (1 = yes) | 0.58 [ 0.16 ; 1.97 ] ( -1.74 ) |
| Log2 geographic distance | 0.88 [ 0.86 ; 0.91 ] * ( -1.13 ) |
| Homophily: GDP lower 25% | 2.34 [ 0.00 ; 3.83 ] |
| Homophily: GDP middle 50% | 1.48 [ 1.32 ; 1.65 ] * |
| Homophily: GDP upper 25% | 1.24 [ 1.14 ; 1.43 ] * |
| Polity score absolute difference | 0.31 [ 0.22 ; 0.42 ] * ( -3.21 ) |
| **NODAL EFFECTS: MATERIAL FACTORS** | |
| Export: Log2 GDP | 1.15 [ 1.03 ; 1.25 ] * |
| Import: Log2 GDP | 0.87 [ 0.84 ; 0.89 ] * ( -1.15 ) |
| Export: Log2 military expenditure | 1.14 [ 1.06 ; 1.25 ] * |
| Import: Log2 military expenditure | 1.07 [ 1.04 ; 1.10 ] * |
| Import: Log2 population | 1.14 [ 1.13 ; 1.16 ] * |
| **NODAL EFFECTS: STABILITY FACTORS** | |
| Import: Sovereignty level (1=high, 0=low) | 0.81 [ 0.74 ; 0.88 ] * ( -1.23 ) |
| Import: Coup incidence (1 = yes) | 1.02 [ 0.91 ; 1.13 ] |
| Export: Interstate conflict (1 = yes) | 0.73 [ 0.54 ; 0.87 ] * ( -1.37 ) |
| Import: Interstate conflict (1 = yes) | 1.44 [ 1.10 ; 1.93 ] * |
| Export: Intrastate conflict (1 = yes) | 0.98 [ 0.88 ; 1.16 ] ( -1.02 ) |
| Import: Intrastate conflict (1 = yes) | 0.90 [ 0.82 ; 0.98 ] * ( -1.11 ) |




**Notes**

a) If *OR* < *1*, the *(-1/OR)* value is given in round brackets to facilitate comparison of OR sizes.
b) M = 122460 (arms transfer tie presence/absence)
c) N = 157 nodes (countries) per time step
d) X-axis is logarithmic-scaled.

***Path dependency in trade relations***. As hypothesised, M5 estimates that countries are 11.1 times less likely to initiate arms transfer with a previously unconnected country, all else in the model held constant (OR = 0.09 [0.09; 0.09] ; logit θ = -2.409 [-2.46; -2.39]). This is evidence supporting hypothesis 13 that countries tend to avoid trading arms with a previously unrelated country, more so than can be expected by chance. All in all, countries seem to be conservative about business relationships when weapons are involved. They show a strong hesitation to initiate new arms transfer relations. It makes sense for states to continue trading with established trade partners rather than forming new ties, as trades in security goods necessitate trust which does not come easily.

### 5.2.2. Dyadic covariates

***Alliance.*** As expected, M5 estimates that an allied country pair is 1.282 times (28.2%) more likely to trade arms than a non-allied dyad, holding all other influences in the model constant (OR = 1.28 [1.15; 1.44] ; logit θ = 0.249 [ 0.14; 0.37]). This supports hypothesis 9a that interstate alliance increases the probability of dyadic arms transfer.

***Armed conflict.*** M5 estimates that, controlling for all else, two countries opposing one another in violent conflict are 1.74 times less likely to transfer arms than a country pair that were never adversaries in armed conflict before (OR = 0.58 [0.16; 1.97] ; logit θ = -0.552 [-1.81; 0.68]). However, since the estimate is non-significant, the effect cannot be established beyond randomness, and thus the null hypothesis is not rejected in favour of hypothesis 9b.

***Geographic distance.*** M5 estimates a probability of a country pair trading arms being reduced 1.13 times given each 2-fold increase in their geographic distance (OR = 0.88 [0.86; 0.91] ; logit θ = 0.12 [-0.15; -0.09]). This supports hypothesis 10 that the greater the geographic distance between two countries, the lower the probability of arms trade between them. This differs from Thurner et al. (2019, p. 1758) who found that geographic distance has no significant impact on arms transfers.

***Homophily by market size.*** There is evidence for separation by economic class the arms trade network. However, this only significantly applies to countries in the middle 50% and in the upper 25% GDP level. M5 estimates that two countries are 1.483 times (48.3%) more likely to trade arms if they both belong to the middle income countries (OR = 1.483 [1.32; 1.65] ; logit θ = 0.394 [ 0.28; 0.50]), while two countries that both belong to the economic heavy weights in the top 25% are 1.226 times (23.6%) more likely to do so than if they were not in the same class (OR = 1.236 [1.14; 1.43] ; logit θ = 0.212 [ 0.13; 0.36]), all other influences considered. This phenomenon is not significant for countries belonging to the lowest 25% GDP class. But overall, there exists discrimination by economic size in the international arms market, whereby countries prefer trading arms with equally developed others. This partly support our hypothesis 7 that two countries belonging to the same market size class are more likely to trade arms with each other than if they were not in the same market size class.

***Homophily by political regime.*** There is evidence that countries prefer to trade arms with politically like-minded others. M5 estimates that two countries are 3.2 times less likely to entertain an arms transfer relationship with every additional absolute regime score difference between them, holding other variables constant (OR = 0.31 [0.22; 0.42] ; logit θ = -1.167 [-1.52; -0.87]). This result fully support hypothesis 4 that the more similar the political regimes of two countries, the higher the likelihood of them trading arms.

### 5.2.3. Country covariates

***Market size (GDP).*** As expected, a state's market size (in USD billions, i.e. $10^9$) is significantly and positively associated with arms export probability in all models. For each doubling of the GDP, a state is expected to have a 1.153-fold (i.e. 15.3%) increase in the odds of exporting arms (OR = 1.153 [1.03; 1.25] ; logit θ = 0.142 [0.03; 0.22]). Yet contrary to hypothetical expectation, market size negatively and significantly affects arms import probability in all models. Each time a state's GDP doubles, its offs of arms import reduces by 15%, i.e. by a factor of 1.15 (OR = 0.87 [0.84; 0.89] ; θ = -0.14 [-0.17; -0.12]).

***Military expenditure.*** Meanwhile, military expenditure (USD millions, i.e. $10^6$) at constant 2021 prices and exchange rates – an indicator for arms supply and demand capacity – is found to significantly increase both arms export and import in all models, as predicted by hypothesis 2a and 2b. For each doubling of a state's military expenditure, its odds to export arms is increased by 14 % (OR = 1.14 [1.06; 1.25] ; logit θ = 0.132 [ 0.06; 0.22]) and its odds to import arms is increased by 7%. (OR = 1.07 [1.04; 1.10] ; logit θ = 0.064 [ 0.04; 0.09])

***Population size.*** Finally, the significantly positive influence of population size (in millions of individuals, i.e. $10^6$) on import probability supports hypothesis 3 against the null. Thus, each 2-fold population growth is associated with a 1.142-fold (14.2%) increase in a state's odds of importing arms (OR = 1.142 [1.13; 1.16] ; logit θ  = 0.133 [ 0.12; 0.15]).

***Internal & external stability.*** Four variables relating to the internal and external stability of a state are assumed to influence the probability of it participating in arms trade: low sovereignty level, coup incidence, international armed conflict, and civil armed conflict. The first one, higher sovereignty score, is significantly and negatively associated with the probability of importing arms. Thus, countries belonging to the upper 50% in terms of sovereignty level are on average 1.23 times less likely to import arms than countries with a low sovereignty score, conditional on the rest of the network (OR = 0.81 [0.74; 0.88] ; logit θ = -0.21 [-0.30; -0.13]). Meanwhile, coup(s) occurrence does not significantly influence arms import probability (OR = 1.02 [0.91; 1.13] ; logit θ = 0.02 [-0.10; 0.12]).

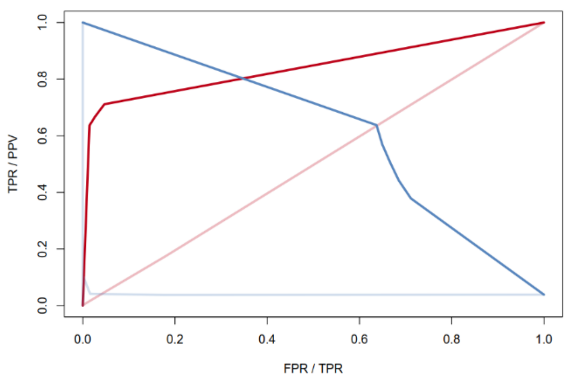
Experiencing interstate armed conflict, i.e. fighting with a foreign state, significantly decreases a state's odds to export arms a 1.37-fold, i.e. by 37% (OR = 0.73 [0.54; 0.87] ; logit θ = -0.315 [-0.61; -0.14]) and significantly increases its odds to import arms a 1.44-fold, i.e. by 44% (OR = 1.44 [1.10; 1.93] ; logit θ = 0.362 [ 0.10; 0.66]). Meanwhile, experiencing interstate armed conflict, i.e. domestic conflict, is not significantly associated with a state's odds of exporting arms (OR = 0.98 [0.88; 1.16] ; logit θ = -0.023 [-0.13; 0.15]). However, having a civil conflict does significantly influence the probability of arms import, albeit in a direction contrary to hypothetical expectation. M5 estimates that intrastate violent conflict significantly decreases the odds of importing arms by 1.11 times, i.e. by 11% (OR = 0.90 [0.82; 0.98] ; logit θ = -0.107 [-0.19; -0.02]).

To summarise, the results support hypothesis 4a (high sovereignty negatively impacting arms import). However, the null cannot be rejected in favour of hypothesis 4b (coups positively influence arms import) or in favour of hypothesis 4d (civil armed conflict negatively influence arms export). Interestingly, hypothesis 4c is discarded not because the effect is non-significant, but because the effect direction is unexpected. That is, civil armed conflict decreases instead of increases the likelihood of arms import. Additionally, both hypotheses 5a and 5b related to the influence of external stability are supported against the null. Armed conflict with a foreign state significantly decreases the probability of export and significantly increases the probability of import. All estimates already considered the remaining influences included in the model.

## 5.3. Model validation

***Out-of-sample model performance.*** The Precision Recall (PR) & Receiver Operating Characteristic (ROC) Area Under the Curve are two established criteria used to evaluate out of sample model fit. (Davis & Goadrich 2006; Sing et al. 2005; Leifeld et al. 2018a, p. 24). For this, the estimated model is compared against that of the Random Model with regards to these two criteria, as depicted in figure 6 (p. 27).

***Figure 6****. M5 Precision Recall (PR) & Receiver Operating Characteristic (ROC)*




The ROC curve of Model 5 (dark red) tell us that it predicts arms transfer presence or absence with ca. 87% accuracy, compared to ca. 50% achieved by the Random Model (light red). The 50% essentially means that its prediction is correct with a 50:50 chance, that is, randomly, while Model 5 predicts correctly 8.7 out of 10 times. By the PR curve, Model 5 (dark blue) correctly predicts arms transfer presence 58% of the time, compared to 3.7% (light blue) by the Random Model. In conclusion, Model 5 that was trained on the t1-t5 network data beats the Random Model in predicting arms transfer ties in the network at t6 by a huge margin, especially regarding the PR criterion, which is more meaningful given zero inflation in the arms transfer network.

## 6. Discussion & Conclusion

Major disruptions of the international economic and political system in recent years have intensified political and academic interest in the trade of strategic goods, notably that of weapons (Mehrl & Thurner 2025, p. 2). Two major events in the past 5 years injected systemic shocks to the global supply chain and trade system – the Covid-19 pandemic and Russia's invasion of Ukraine. The latter is felt as an assault on the European security order and altered international arms flows. Yet so far, no investigation has covered the arms transfer network of the past 5 years. The current study sets out to close this gap.

The study tracks the evolution of the PCW international arms market, using a longitudinal design to analyse arms transfer decisions of 157 countries. It examines the effect of external drivers on the probability of international arms transfers while holding constant internal network dependencies, including temporal trends. To this end, a sequence of temporal exponential random graph models (TERGM) was built, with latest round of SIPRI arms transfer data (SIPRI 2024a) as input. The network time series consists of six time steps, each containing arms transfers data aggregated over a five to six years' time span within the 1993-2023 period.

The network-political economy model of arms trade of this paper is informed by international political economy and network theories. On the political economy side, the supply and demand model of arms trade by Levine et al. (1994) is leveraged, including its formalisation in the gravity equation (Isard 1954; Tinbergen 1962; Linneman 1966; Poyhonen 1963). On the network side, this paper's model follows the suggestion of Ward et al. (2013) to integrate network dependencies into the gravity equation of trade. Subsequently, Thurner et al. (2019) draw on the extended gravity model of Ward et al. (2013) to derive a network political theory of arms trade. They then used TERGMS on the global arms trade network between 1950-2013. This paper takes up from there. In contrast to Thurner et al. (2019) however, this paper samples exclusively PCW arms transfers to single out effects specific to the post-1992 international system.

This paper's working model is dubbed the "network-political economy model of international arms transfer" and formalised as an TERGM. The model's left-hand side outcome is the binary decision to trade arms between any given country-dyad. The right-hand side includes traditional variables from the gravity model of trade and extended with geopolitical factors. Country covariates are domestic market size, national military spending, population count, and domestic stability indicators (sovereignty score and coup experience), as well as participation in armed conflicts. Relational covariates include interstate alliance agreements and interstate conflict episodes, geographic distance, homophily by economic class, and homophily by regime similarity. Network and temporal dependencies include outdegree, indegree, reciprocity, hierarchical triadic closure, linear expansion, and path dependency terms.

This study provides four main contributions to the research of international arms transfers networks, both theoretical and empirical. First, it systematically reviews the literature on the international arms transfer network research, thereby giving the reader the state of the art on the subject. Thurner et al. (2019) are the first to apply an inferential model appropriate for graph data to analyse the arms trade network. Since then, research in this domain has grown but remains scant.

Second, this study adds new theoretical propositions to the arms trade network model. First is the hypothesis that economic class homophily exists in arms trade relations, as derived from Marxist IEP theory. Indeed, the study finds that countries tend to trade arms with others of similar market size. However, this effect is only observed for countries that belong to the middle and high income classes, i.e. if they belong to the upper 75% of the world GDP ranking. Less developed countries that belong to the lower 25% GDP class do not show this assortative arms trade behaviour. This may come from their limited ability to produce and/or purchase weapons because these product necessitates a minimum level of economic development. Hence, countries belonging to the “lower” GDP class may not be able to participate in the arms trade market as extensively. The next new theoretical proposition by this paper is that different dimensions of armed conflict involvement, such as the causes, type, and intensity of the conflict, may have different impacts on countries’ odds of trading arms. Additionally, this paper explores two new markers of countries’ internal political stability which are coup experience and sovereignty level.

Third, the study provides and contextualises different centrality and centralisation measures – descriptive statistics that are a staple of network analysis but are missing from previous studies. This paper finds that countries’ relative importance in the arms trade network changes depending on how that importance is defined – including 1) indegree and outdegree centrality (attracting many importers or exporters), 2) eigenvector centrality (connection to influential network members), 3) betweenness centrality (brokering between unconnected states in the supply chain), and 4) closeness centrality (quick and efficient access to trade partners). The detailed analysis differentiates this paper from previous studies that focus solely on traditional degree centrality measure, neglecting the other aspects of network influence.

Fourth, this study provides an analysis for the complete post-cold war era, with the ambition of discerning features that distinguishes the network of this period from others. Data of Cold-War and post-Cold-War periods were routinely pooled in models of earlier research. This study is the first to provide a separate analysis for the complete post-Cold War arms transfer network. In doing so, it shed light on the similarities and the differences between networks that are embedded in two different geopolitical settings.

In terms of similarity, this paper found that enduring endogenous attributes of the network that apply both to the Cold-War and post-Cold-War samples are low out- and indegree, low trade reciprocity, high nested transitivity, and high path dependency. These results agree with earlier studies (e.g. Thurner et al. 2019, p. 1746, p. 1758; Lebacher et al. 2020, p. 208; Lebacher et al. 2021, p. 215). Also similar to earlier studies, country attributes found to have a significantly positive association with arms import probability are military expenditure level, population size, and participation in an international conflict, while higher sovereignty level has a significantly negative association with arms import probability. On the export side, attributes like market size (GDP) and military expenditure have a significantly positive association with arms export probability, while participation in an international conflict has a significantly negative association with arms export probability. As for relational attributes, two states' are more likely to trade arms if they are allies, whereas they are less likely to trade arms the higher their geographic distance and regime differences.

As for the differences, this study finds two effects that deviate from or even completely contradict prior findings. Among them, two significant effects stand out. First, the growth of a state's domestic market size does not increase, but actually decreases the probability of it procuring foreign weapons. The implication is that contrary to widely held beliefs, a state's economic output does not always positively relate to its arms demand, and by extension, to its defense spending level. This may have been the case during the cold war era, but not in the post-cold war era.

Second, being involved in an armed conflict does not necessarily increase, but may even significantly decrease the probability of a state importing weapons. The relationship between states' participation in armed conflict and their weapons trade behaviour is moderated by additional features of the armed conflicts, such as their type, cause, and intensity. Overall, except for international and government-related armed conflict, no other type of conflict has an impact on export probability. More importantly, except for international armed conflict, all other conflict types have a significantly negative impact on import probability, which goes against hypothetical expectations. Any theoretical intuition regarding states' arms import and export decisions only applies consistently when they are involved in international conflict. This implies that we must reconsider the commonsense assumption that countries in experiencing conflict situations automatically purchase more and sell less weapons. In theory, experiencing armed conflict should intensify a state's need to stock up its armoury and reduce its willingness to export its remaining arsenal, regardless of the causes and extent of the conflict. Yet this proposition only hold true for the Cold War period.

These two findings highlight that network effects may not generalise across time periods. Accordingly, future studies should consider structural breaks when analysing international arms transfer relations as they are different depending on the different political and economic realities they are embedded in. For instance, by checking latest news on the current geopolitical situation, one may get the impression that security and political determinants have gained relative weight in the calculus of arms trade decisions at the expense of economic factors, reminiscent of the cold-war era. Or, an entirely unknown arms trade pattern may have emerged, and with it the need to revise policy and adapt theory altogether. Theory and empirical analysis should control for these structural differences in the future. References

The following reference list includes a) bibliography, b) source of datasets, and c) most important softwares and packages used in data preparation and analysis. Please consult the R markdown files available as supplementary material for detailed information on all packages and functions used for data preparation, analysis, and visualisation.

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### b. Datasets

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### c. Softwares

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