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Political Distance in the Network of International Trade

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Abstract: This study is concerned with the underexplored link between political distance and international trade. It considers the network of international trade which is investigated using Temporal Exponential Random Graph Models. While related to gravity models in the data used as well as the choice of covariates, this allows for greater insight, particularly into higher order dependencies in the network of international trade, considering not only dyadic country pairs but the network as a whole. The results suggest a negative relationship between political distance, based on a measure of difference in votes at the UN General Assembly, and the probability of a trade tie. Additionally, it finds that this effect is present when political distance is defined using the democratic scale of the Polity V dataset, but for the autocratic scale only at more granular levels of industry. The network model suggests a grouping of countries with low political distance having the strongest effect on the likelihood of a trade tie, giving support to the relationship between democratization and an increase in trade activity. Additionally, it suggests that countries that are distant in the democratic scale are integrated into the international trade network to bind them to the international order, given they are not far apart in the autocratic scale, a basis for weaponized interdependence exclusive to democratic states. The results highlight the importance of political distance in international trade and the role of politics in trade relationships as a factor in the likelihood of ties between countries.

Keywords: International Trade, Network Analysis, International Relations, (Temporal) Exponential Random Graph Models, Gravity

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1 Introduction

International trade as a field of study in (international) economics has been concerned with the determinants of countries' trade as a prime subject of inquiry Historically, this has spurred several theories of trade that draw on a rich intellectual history and has culminated in the establishment of gravity theory as the workhorse model used in international trade today (e.g., Antràs 2016; Yotov 2022). The central feature of all the gravity models is the consideration of dyadic country pairs and their bilateral trade, taking into account effects of their embeddedness in international trade only on the level of shared characteristics (e.g., common language, religion, or colonial history) (Head and Mayer 2014). The focus on bilateral trade permeates through the study of international trade as a whole. Trade, however, does not follow a framework of isolated bilateral flows that are solely shaped by effects between a country pair. Rather, it has an inherently social aspect in that it is taking place in the network of international trade with countries as actor on the international plane setting boundaries and incentives to trade, forming relations that are influenced not just by shared characteristics but also the structure of these relations themselves, giving rise to the network structure of international trade (Bhattacharya, Mukherjee, and Manna 2007; Chaney 2014).

A focus on bilateral tradeflows and their consideration as the sole relation in international trade then risks overlooking higher-order dependencies, which could either occur on a secondary level between countries in a dyad and external countries or on a tertiary level between countries outside of a dyad, which nevertheless impact trade between two states. Accounting for these factors that occur outside of a dyadic pair of countries, social network analysis has been taken up as a way to gain insights into the mechanics of international trade (cf. Herman 2021). It allows for the consideration of determinants external to a pair of countries both in the trade network, as well as other networks that connect countries among each other, in each case also considering higher order dependencies. Thereby, it gives a fuller picture of the mechanics of trade within the reality of a complex international network that is formed by the multilateral environment in trade.

In the study of trade in a gravity-like setting, a typical set of determinants investigated includes a mix of economic, spatial, historical and organizational distance variables. This encompasses GDP of the trade partners; distance and possible contiguity; shared colonial, linguistic, and legal history; as well as organizations of international trade like the General Agreement on Tariffs and Trade (GATT), the World Trade Organization (WTO), or the European Union (EU)[1] and Regional Trade Agreements (RTAs) that a country pair has shared membership in. What has received less attention is the impact of political distance between countries on their trade flow. While some of the effect of political proximity is captured through the organizational variables included in trade analysis, this does not take into consideration the impact through channels other than reduced trade barriers. In fact, in the formation of RTAs, political proximity itself is a determinant that is realized through the formation of an RTA between nations that are politically close to each other (Gowa and Mansfield 1993; Maggi and Rodriguez-Clare 2007; Mansfield, Milner, and Rosendorff 2002). Other effects can, however, also occur, where previous literature has identified an impact through channels such as the governance environment (Li and Samsell 2009; Wu, Li, and Samsell 2012, 2012) and rule of law considerations (S. Yu, Beugelsdijk, and Haan 2015; Anderson and Young 2000) on the risk assessment by firms, individual choices spurred by emotions elicited by politicians that are antagonizing other countries impacting the trade with those countries (Pollins 1989), or geopolitical considerations on security externalities from trade (Haim 2016). Political distance then has an effect separate from that measured

[1] The EU is not an organization of international trade in a strict sense but, because of its predecessor organizations, especially the European Economic Community/European Community (EEC/EC), shares characteristics with them, like a customs union, which have been deepened through the subsequent political cooperation lowering barriers to trade, motivating its inclusion but also separation from other RTAs.

through variables such as shared RTAs, even more so when considering the network nature of both trade and international politics.

The motivation to study the impact of political distance on trade stems on the one hand from theories of international trade and international relation that are concerned with the underlying causes for trade between nations. On the other hand, it is related to work in international security relying on networks as structures that bind nations and can be weaponized (Farrell and Newman 2019). Investigating the origins of trade ties that form a network on their own, but are also the counter-structure to a number of financial networks, the aim of an investigation into the political determinants of the network of trade ties between nations is to shed light onto the causes for the shape of these weaponizable networks. The question raised is whether politics, in the form of political distance, is a factor in the shape of the network of international trade.

2 Literature

Two strains of literature are relevant in the context of the analysis of international trade's network structure. On the one hand, literature on determinants of international trade, chiefly among them the gravity-related literature, is of interest insofar as it pertains to the explanatory part of the analysis. It serves as reference and comparison to insights that are gained through network analysis, having a well-established concept and results that have been used widely in the investigation of causes for international trade. The latter allow to contextualize the analysis carried out in both its motivation and conclusion. On the other hand, works on network analysis and particularly those being concerned with trade relationships, either in an economic or political context, have a connection through the methodological side to the analysis presented in this work. They serve as background to the methods and their use-cases, in order to situate this study from a technical point of view. Each literature will be presented and surveyed in turn.

2.1 Gravity

The origin of the gravity literature in trade lays with the seminal work of Tinbergen (1962), who introduced gravity equations as as a method to explain empirical facts relating to international trade, namely the impact of European integration.[2] While rooted in empirical work and (appearing to) borrow from physics in an analogy that gave narrative legitimacy to observed patterns, the theoretical economic foundation was only laid later. Anderson (1979) introduced an economic model of gravity, yet did also not find recognition among trade economists (Head and Mayer 2014, 8). Both these works, however, spurred further research into gravity as a concept in international trade, which culminated in contributions to the edited volume by Grossman and Rogoff (1995), where puzzles that the gravity literature set out to account for, namely the importance of distance and multilateral resistance, were raised and shortly after answered in the contribution setting the standard for gravity methodology by Anderson and Van Wincoop (2003) and Eaton, Kortum, and Kramarz (2004), who set the micro-foundations for gravity (cf. Head and Mayer 2014, 8–10). This heralded a time period of strong research activity for gravity models of trade, where gravity became a workhorse model for a number of contributions to the trade literature dealing with an array of possible determinants. The numerous contributions are contemporaneously surveyed by Anderson (2011) and Bergstrand and Egger (2013), as well as more fully reviewed by Yotov (2022, 3–9), whose review article is referred to for a comprehensive overview of gravity literature, both empirical and theoretical, outside of the scope of this study. During this "golden age of 'Structural Gravity' " (Yotov 2022, 5), a number of determinants of trade have been studied, among them distance, free/regional trade agreements, memberships in

[2]Note that while seminal for international trade, the desire to incorporate gravity as a natural law from physics is both wider and older. It is related to the concept of "social physics" (Krugman 1997), which aims to find "natural laws" for economic relations that are akin to physics' natural laws, which span a number of schools of thought in economics (Bergstrand and Egger 2013; Yotov 2022). The aim of the incorporation of networks is, in fact, counter to the desire for natural laws, inasfar as it treats actors as social, giving credence to their interaction in determining outcomes.

international organizations, chiefly the GATT/WTO, and colonial relationships (cf. Yotov 2022, 5–6).

While the gravity literature has concerned itself amply with institutions and economic variables, politics as a determinant has not received equivalent attention (cf. Umana Dajud 2013, 284). The earliest such work by Dixon and Moon (1993) looks at the United States' trade partners and the importance of similarity in political systems and foreign policy. They are using voting agreement from the United Nations General Assembly to calculate correlation in foreign policy and the democracy scale of the Polity II dataset to do the same for similarity in political systems (Dixon and Moon 1993, 13–15). Morrow, Siverson, and Tabares (1998) use similar indicators to test for three possible determinants: presence of a military dispute, common interests measured through their set of alliances, and again the democracy scale of the Polity II dataset (1998, 653–54). Both Dixon and Moon (1993) and Morrow, Siverson, and Tabares (1998) find that closeness in their measures of democracy and foreign policy increase trade with the US and among major powers, respectively. Bliss and Russett (1998) also confirms the results pertaining to shared democracy, using a composite of the autocracy and democracy score of the Polity III dataset. Importantly, all three of these studies consider the time period leading up to 1990[3]. This has two problematic implications. On the one hand, as Umana Dajud (2013, 285) notes, could there be problems in the measurements of trade flows in the (early) 20th century. Additionally, from a historical point of view, the time period study was characterized by both strongly increasing trade as well as strong democratization. Accordingly, Decker and Lim (2009), studying the period 1948-1999 and finding a positive relation of democracy as measured by the Polity IV dataset and trade, note that there is a difference in the pre- and post-1990 period with a sign change when partitioning the dataset. This was also found by Shenglang

[3]Dixon and Moon (1993) studies 1966-1983, Bliss and Russett (1998) 1962-1989 and Morrow, Siverson, and Tabares (1998) 1907-1990.

(n.d.) when comparing trade before and after the Cold War. Later studies confirm these previous findings with extended datasets. Of note is work by M. Yu (2010), who uses the Polity IV dataset again to measure democratization and finds an impact on exports, investigating democratization and trade and finding, using the measures from the Polity IV dataset and accounting for endogeneity, an increase in trade, specifically exports, that goes along with democratization. Most related to this study, Umana Dajud (2013) uses a set of indicators for political distance and a research design that aligns with the gravity literature, specifically the inclusion of multilateral resistance terms. With this methodology, he finds that political distance defined by UN vote correlation as well as based on several political scales has an impact in the expected direction, with more politically close countries trading more, with the caveat that this becomes weaker when the costs of reducing tradeflows rise. Some studies focus on specific industries, for example Akerman and Seim (2014), which find an increased trade in the arms industry between trade partners that are politically close in the past, though less so today. Finally, Chen and Zhou (2021) calculate a score based on rare events to measure a country pair's friendliness in a gravity framework, finding that imports increase with friendliness, while raising the importance of internal political as well as international organizational constraints that limit possibilities of political friendliness between countries to influence trade. Importantly, they note that this effect, acting through WTO membership, is present in democratic states, while absent in authoritarian ones, with this divergence also present in the magnitude of the impact they measure.

One particular strain of gravity literature has arisen out of the insight that network structures are relevant in trade, and the international trade network (ITN) can be an important framework to gain insights into the motivations and determinants of trade (cf. De Benedictis and Tajoli 2011; Chaney 2014). Fagiolo (2010) uses the residuals of a gravity model to weigh a network and then applies network analysis to this "residual network" in order to explain patterns that are not already explained by the gravity equation, finding that small, specialized and trade-oriented countries are dominant players in this network, as opposed to the big trading partners in the ITN. Subsequently, Duenas and Fagiolo (2013a) investigate whether gravity equations are able to predict network properties of international trade, which is not the case unless the structure of the ITN remains fixed, leading them to conclude that other methods need to be incorporated to explain topological properties. Ward, Ahlquist, and Rozenas (2013) does so, observing that network dependencies are ignored by gravity models, by combining a gravity equation with network sender and receiver effects, finding that such a model has higher explanatory power compared to a "pure" gravity one. Taking this concept further, Almog, Bird, and Garlaschelli (2019) introduce an "Enhanced Gravity Model" in which they combine gravity and network approaches to explain the volume and topology, respectively, of the ITN, combining a gravity equation with maximum-entropy network models. This allows them to reproduce the structure of the network as well as the edge weights, i.e., the trade volume.

2.2 Network Analysis

In contrast to literature centering gravity as a way to explain trade patterns, more recently network analysis has been a tool that is used to gain insights into the complexities of the international trade network. De Benedictis and Tajoli (2011) note that networks have been a frame of reference for economists to think about trade for a long time and proceed to use network analysis to reveal and study features of the World Trade Networks topology, importantly the role of the WTO in network formation. De Benedictis et al. (2014) continue this investigation using the BACI dataset (for details on the dataset's structure see the data below) and studying a number of network measures. Both of these studies were important in setting network analysis as a method when looking at the ITN. However, they did so in only a descriptive way, analyzing the network, rather than through statistical inference.

In the study of networks, ERGMs are becoming increasingly favored as a tool to conduct analyses with statistical inference. As Panuš and Dymáková (2017) note, ERGMs are an apt methodology to study the ever-more complex networks that are present in international trade and serve as a useful vehicle in order to understand the structure of the ITN. They have, however, not been adopted widely in economics and thus also not in the study of international trade and the ITN (Herman 2022; Pol 2019). Ghafouri and Khasteh (2020) conduct a wide survey of uses of ERGMs based on several previous surveys and spanning different fields, where in the domain of economics applications contributions in business studies are more numerous compared to other sub-fields; Pol (2019) also notes the diverse topics. Not mentioned by either are studies in the field of arms control that look at the arms trade network, finding a resurgence of political security concerns over economic ones in weapons sales starting in 2001 (Thurner et al. 2019; Lebacher, Thurner, and Kauermann 2021). For international trade, Pan (2018) investigates the impact of different kinds of international organizations on trade, finding that preferential trade agreements play a more important role than organizations like the WTO. Related to this work, Cranmer, Desmarais, and Menninga (2012) earlier used ERGM when analyzing alliance formation, finding the counter intuitive effect that joint democracy decreases the likelihood of alliances[4] when using an ERGM, as opposed to a positive effect in a logit regression (as well as other differences in effects between the two methods). They also note a positive effect of trade on alliance formation. M. Smith, Gorgoni, and Cronin (2019) uses a multilevel ERGM to show the importance of firm ownership structure and trade for a specific industry. Overall, while still scarce, especially compared to the gravity literature presented above, network approaches have potential to explain characteristics of the ITN not accounted by other literature.

[4] While going against their expectation, the negative effect is explained with the lessened need between democracies to form alliances, as they do not pose a threat to each other that would be mediated through an alliance (Cranmer, Desmarais, and Menninga 2012, 307; for the theoretical argument see Gibler and Wolford 2006).

2.3 Synthesis

Herman (2022) compares gravity models and ERGMs in studying international trade, using a similar specification for both in order to analyze their respective strengths and weaknesses. This work is most pertinent and related to this study not only because of the comparison showing where ERGMs hold value in the analysis of trade data, but also because it is one of the few contributions to network literature that use ERGM in a trade context, which makes it methodologically analogous to this investigation. He finds, concurrently with the results from Almog, Bird, and Garlaschelli (2019), that network models allow important insights into network dependencies that are missed by gravity models. ERGMs are especially insightful about the ties between countries and their characteristics, as well as in the distribution of shared partners. Gravity models show a better performance for the estimation of geodesic distance between countries, with the inclusion of network characteristics in a gravity equation being a middle point between a pure gravity model and an ERGM. Thus, for an investigation concerned with attributes of ties between countries, such as in this case, an ERGM presents itself as the most appropriate choice.

3 Methodology

To investigate the impact of political distance on international trade in a network context, i.e., on the international trade network, networks as the object of interest in the inquiry and (temporal) exponential graph models as statistical tools are considered. Statistical inference within network objects require models that take into account the structure of a network when estimating determinants. The choice of model, motivated both by the literature as well as the subject of interest, is an Exponential Random Graph Model as well as its complement for network time-series, the Temporal Exponential Graph Model, which are introduced below. In addition, the construction of networks requires relational data that defines the edges of the network. As the unit of analysis in gravity models is a dyad of countries, datasets that are used for gravity model estimations can also be employed when creating the network objects to be investigated. The model that is used to shed light on the determinants in the ITN is based both on network analysis as well as variables that are of interest due to their presence in and demonstrated relevance by gravity models of international trade. The model is then estimated using statistical packages developed for inference with network objects and forming part of a growing environment of network analysis methods.

3.1 Networks

Networks form a class of statistical objects that represent relational data. A network is a set of N actors that are connected through the realizations of a random variable Y_{ij}, where (i, j) is an ordered pair of the set of actors, with $i, j = 1, \dots, N; i \neq j$. Such a network can then be represented in one of two ways. Either as an edgelist with ordered actor pairs and their realization of the random variable, or through an adjacency- or sociomatrix of dimensions $n \times n$, where the diagonal as the self-ties of actors to themselves are treated as structural zeros. A network can either be directed or undirected, the difference being illustrated through the symmetry of the adjacency matrix. If the matrix is symmetric, $Y_{ij} = Y_{ji}$ and thus the direction of the tie is not considered, i.e., it is an undirected network, whereas if $Y_{ij} \neq Y_{ji}$ the tie can be different depending on the direction and has a direction. Graphically, a network is represented through nodes n_i and edges or vertices $e_{i,j}$, where each actor is a node that can be connected to $1, 2, \dots, n-1$ other nodes or actors, with each connection being an edge of that network and representing a tie Y_{ij}. There are a number of different shapes such a tie can take. Importantly, it is not only restricted to a dyad, but can also take into account (multiple) other nodes, thereby accounting for the endogeneity of the random variable.

3.2 Exponential Random Graph Models

Exponential Random Graph Models (ERGM) are a family of statistical models that are used for statistical inference on networks. The intention of ERGMs is to estimate covariate effects similar to a regression, while at the same time taking into account the special features of a network, where outcomes are not exogenous of each other but rather exhibit interdependence. The ERGM avoids a faulty inference that can be present when using regression analysis alone, where only a dyad is considered, and effects that occur outside of this triad are neglected, as they cannot be fit into the framework. In this case, a bias is introduced into the regression results, as the model is misspecified due to the omission of relevant structural effects.

In the literature, including the one outlined above, two alternative ways to account for the structural effects of networks have been used. On the one hand, some studies use standard error clustering [5], which, however, does not correct for the structural misspecification that arises from the non-independence of nodes in a network (Cranmer and Desmarais 2011, 67). On the other hand, network statistics have been included in regression analysis with the goal to account for network effects in its estimation[6], which, however, also does not solve the problem of the independence assumption inherent in regression analysis but absent from networks. This approach is causing further problems by calculating network statistics first to include them in the regression analysis, assuming an exogenous nature of these statistics that are, in fact, inherent to the structure of the estimated variable as features of the network whose realization is estimated (Cranmer and Desmarais 2011, 68). Because of these shortcomings to alternative tools that use regression analysis to model networks, ERGMs remain as "true" network models to conduct statistical inference on social networks.

[5]This is for example done by Haim (2016), who forgoes ERGMs in favor of this approach when analyzing the effect of alliances.

[6]Such an approach is carried out by Duenas and Fagiolo (2013b), who include network statistics in their gravity regression to account for the network structure of international trade, whose relevance they recognize.

The basis for an ERGM is naturally a network, denoted as $\mathbf{Y}$, which can be represented using an $n \times n$ adjacency matrix as outlined above. This network is treated as one of M possible realization from the set of n nodes observed, forming the support Y_M of a stochastic process, that gives the edges of the network. Of interest is the impact of a number of network statistics Γ_k on the likelihood of the observed realization of the network Y. The observed network statistics $\mathbf{\Gamma}$ from $\mathbf{Y}$ are then assumed to be the expected network statistics of all possible networks $Y_m \subset Y_M$, so that $\mathbb{E}[\Gamma_k] = \Gamma_k \forall i$, which is sensible as the observed realization is the only observable one and thereby the best, because only, guess for its true value. The identifying condition then is:

$$\mathbb{E}[\Gamma_m] = \sum_{m=1}^{M} P(Y_m)\Gamma_m$$

for the probabilities of all networks in the support $Y_m \subset Y_M$, and particularly for the observed realization of the network $\mathbf{Y}$, whose probability can be calculated as:

$$Pr(Y_m|\theta) = \frac{\exp[\theta^{\mathrm{T}}\Gamma_m]}{\sum_{m=1}^{M} \exp[\theta^{\mathrm{T}}\Gamma_m]}$$

where θ is the vector of model coefficients that relate $P(Y_m)$ to the network statistics Γ_m. (Cranmer and Desmarais 2011; Park and Newman 2004)

3.3 Temporal Exponential Random Graph Models

In order to consider networks over time, Temporal ERGMs (TERGMs) can be utilized to extend the ERGM framework to include a number of networks observed anteriorly to the one under consideration. To do so, a temporal superscript is introduced and the probability now does not depend on the network statistics Γ_m, but rather on network statistics taken into account K previous networks so that $\Gamma_m^t = g(Y_m^t, Y_m^{t-1}, \ldots, Y_m^{t-K})$.

Then, the probability for the network realization at the t becomes:

$$Pr(Y_m^t | Y_m^{t-1}, \dots, Y_m^{t-K}, \theta) = \frac{\exp[\theta^{\mathrm{T}} \overbrace{g(Y_m^t, Y_m^{t-1}, \dots, Y_m^{t-K})}^{\Gamma_m^t}]}{\sum_{m=1}^{M} \exp[\theta^{\mathrm{T}} \underbrace{g(Y_m^t, Y_m^{t-1}, \dots, Y_m^{t-K})}_{\Gamma_m^t}]}$$

where the probability takes into account previous realizations of the network up to that point in time. To arrive at the joint probability of a sequence of observed networks $\mathbf{Y^T}$ the probabilities of the T separate realizations are multiplicatively combined to give (with the subscript dropped for better readability):

$$Pr(Y^{K+1}, \dots, Y^T | Y^1, \dots, Y^K, \theta) = \prod_{t=K+1}^{K} Pr(Y^t | Y^{t-1}, \dots, Y^{t-K}, \theta)$$

The TERGM, much like an ERGM, estimates the parameter θ in order to relate the network statistics, which can be either exogenous or endogenous to the network, to the realization of the network, i.e., the observed network. (Leifeld, Cranmer, and Desmarais 2018; Cranmer and Desmarais 2011; B. A. Desmarais and Cranmer 2012; Hanneke, Fu, and Xing 2010)

Similar to an ERGM, when estimating a TERGM it is necessary to simulate all possible networks from the set of nodes present in the realization of the network. As in TERGMs the probability becomes multiplicative and dependent on t potential numbers of networks, the resources necessary for the estimation also increases. In order to ease the computational burden, the estimation can be bootstrapped, relying on the Maximum Pseudo-likelihood Estimation (MPLE) (cf. B. A. Desmarais and Cranmer 2012; Leifeld, Cranmer, and Desmarais 2018, 7). This is an alternative approach to the Markov Chain Monte Carlo implementation employed by ERGM estimation that allows for faster estimation. In settings with large n or t, so either a large number of nodes or many time steps, the two estimation techniques converge, giving a consistent estimator (Strauss and Ikeda 1990; Hyvärinen 2006).

3.4 Data

In order to construct the networks of trade data as well as covariates a number of data sources are used. Given the similarity to gravity estimation in the concept (albeit not structure), established gravity datasets that are maintained form the central data source for the trade networks. These also hold data that is used for covariates as a number of controls. In addition, political distance as a quantitative concept in political science has to be measured. The period under consideration was set at the greatest possible time range of the data sources. In order to construct the network for the TERGMs, it is important that the set of nodes under consideration stays the same for all time periods. Therefore, the geographical focus was narrowed to the set of countries where the data sources provide data for all time periods, without interruption or entry or exit during the time period.

3.4.1 Gravity-style data

With the intention to stay consistent with the literature on international trade in a gravity context as well as to make sure the data is maintained, the standard gravity dataset from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) is used (Head and Mayer 2014). The dataset holds data on trade flows as well as a number of variables that are used in the model. The variable weighted distance is constructed by Mayer and Zignago (2011) taking into account the distribution of the population within a country to calculate a distance measure that is dependent on the size of the cities' of a country. The variable common language is a dummy constructed by Mayer and Zignago (2011) that counts languages with at least 9% of the population of a country in a dyad speaking it as common between the two. The contiguity variable is dependent on shared border between a country pair and also calculated by Mayer and Zignago (2011). These variables are not updated since the publication and thus static for the years following 2010 (Mayer and Zignago 2011; Head and Mayer 2014, 12). Additionally, data on RTAs is included from the database maintained by the WTO, which includes 559 trade agreements in the version used, which are then narrowed down to 525 RTAs that are included in the dataset based on information relating to signatories. It is current as of 2020 (Head and Mayer 2014). Data on GDP is taken from the Penn World Tables version 10.0, due to consideration of a broad geographic and temporal horizon. The variable used is the real GDP on the expenditure side, relating to the terms of trade of countries, which more accurately reflect the interest in this study about the influence of economic size of a country to its trading ties (Feenstra, Inklaar, and Timmer 2015). The trade data is collected by CEPII in the Base pour l'Analyse du Commerce International (BACI) database, which uses the UN Comtrade tradeflows and corrects them for inconsistencies in reporting of exports and imports for the same trading partners. This is related to differences in the International Commercial Terms of reporting of exports and imports, where the two values are reconciled using an estimation of CIF (cost, insurance, freight) costs which are included in imports but not in exports and therefore substracted (Gaulier and Zignago 2010). This data is extracted separately from the gravity dataset in order to reshape it to the form necessary to construct the network. The data is available in different goods classifications of the Harmonized System (HS) of products (Chaplin 1987) that originated from customs classification. The years available for the BACI dataset span from 1995 to 2020. In order to include all years, the HS92, the iteration of the Harmonized System from 1992, is used, where all subsequent years are available in this classification.

3.4.2 Political distance data

In order to measure the similarity of political positions, the views of nations' governments need to be measured and translated into a quantitative measure. While qualitatively describing a government's position is a task that has a wealth of possibilities, doing so quantitatively necessarily restricts the ways of doing so, as a reduction of dimensions is necessary to arrive at a quantitative measure. Bailey, Strezhnev, and Voeten (2017) use the recorded votes of governments in the UN General Assembly (GA) to carry out such a dimension reduction, arriving at a uni-dimensional measure that estimates the ideal point of each state and allows the calculation of a distance between these ideal points, thereby giving a way to measure the political distance between two nations. This data is available for all UN GAs until the 75th session, which took place in 2020, with the last session not yet fully coded and still subject to difference. Hence, the data is only included until 2019[7] Following the approach chosen by Umana Dajud (2013), this difference based on UN GA votes is supplemented by another measure of difference between states, namely between their regimes. In order to do so, the Polity dataset (Marshall and Gurr 2020) in its 5th iteration is used, which is based on work going back several decades (Eckstein, Gurr, et al. 1975) of manual coding of polities' authority characteristics. While a combined score has often been used, the original rationale by (Eckstein, Gurr, et al. 1975) is based on the separate treatment of democratic and autocratic characteristics , which are thus treated as two separate measures of political distance. This data is available for the time period until 2018. The Polity project has received various criticism for its coding, among them inconsistency over time and a bias towards some nations. Since the period under consideration is a fairly short one, the inconsistency has little time to take hold. Additionally, any bias towards some countries are, in fact, also not a problem for the results as they just mirror a general attitude that can be seen as part of the political distance between countries.

[7] This also allows for foregoing the inclusion of the year 2020 with a marked slowdown in trade due to the government actions containing COVID-19.

3.5 Model

The model that is investigated is informed by the findings of the gravity and network literature presented above. In order to describe the ITN, a set of attributes needs to be selected to be included in the model, which can be either topological, describing the network itself, or social selection attributes, which relate the network to other characteristics that influence the network's edges (Lusher, Koskinen, and Robins 2013). The "standard" determinants of trade as investigated by the gravity literature include distance, common language, colonial links, contiguity, and shared RTAs as well as international organizations like GATT/WTO and the EU. Accordingly, all of these variables are also included in the ERGM. Additionally, the variable of interest is the political distance, which is included as the correlation of UN votes and the Polity V variables. These form the social selection attributes of the network. In order to account for network-specific dependencies, a number of topological attributes are also included. The topological variables of the model are the number of mutual degrees (mutuality), the number of balanced triads (balance) and the number of transitive triads (transitivity). The relation associated with these terms is detailed in Table 1. They serve as descriptors of the network itself, being determined by the edges and thus the relations between the nodes of the network, the countries of the ITN.

Table 1: Types of topological attributes

Term	Node relation
Mutuality	$a \leftrightarrows b$
Balance	$a \leftrightarrows b \leftrightarrows c, a \leftrightarrows c$
	$a \leftrightarrows b \not\leftrightarrows c, a \not\leftrightarrows c$
Transitivity	$a \leftarrow b \rightarrow c, a \leftrightarrows c$
	$a \rightarrow b \leftarrow c, a \leftrightarrows c$

The three terms thus give insight into the configuration of trade from itself, void of any outside influences. All three are related to the reciprocity of trade ties and are standard measure in the network literature. Mutuality can provide an explanation of the importance of a reciprocal edge in a node, or country, dyad, and thus whether trade flows in both directions of a tie. This is to be expected when trade elicits countertrade. The function of balance and transitivity is similar but also holds an important distinction. Balance is a measure of trade occurring “through” a partner, with a reciprocal edge, or trade (non-)relationship, in one dyad occurring concurrently with a reciprocal edge, or trade (non-)relationship, between one node of that dyad and a third node. It can be seen as a measure of the strength of alliances in the network, where alliance partners jointly either include or exclude a third country. Transitivity is similar to this, measuring whether a pair of edges that are either incoming or outgoing from or to a node implies that there is a reciprocal edge between the partners of the node in both vertices. Such a node would have exhibit a higher centrality in the trade network and could be seen as either a hub that trades with interconnected trade partners, being either a strong exporter or importer.

The social selection attributes of the model are more closely related to the gravity literature. As a fundamental insight of gravity models, logged GDP is included as an attribute for each node. The model includes both the level of GDP as well as the difference of GDP in a dyad as potential determinants. While the first tests the standard gravity result of bigger countries trading more, the second is a measure of the grouping of small and large countries. Related to the fundamental gravity finding is the denominator in the simplest possible gravity models, the distance in a dyad between trade partners, weighted for the economic activity in each country. Additionally included are a number of relations that are present in the gravity literature and have been shown to impact trade. The common language in a dyad is measured based on speakers (rather than recognition as official language), with an edge being coded as having a common language if at least 9% of the population in both node countries speak it. An edge is further coded as contiguous if both nodes of that edge share a border and are thus geographically contiguous. Finally, an edge is coded as being associated to an RTA if both node countries share membership in a regional trade agreement. (Head and Mayer 2014)

In order to account for the political distance, two measures are employed as outlined above. For the distance between the ideal point of voting in the UN GA, simply the measure is included as outlined above. In the case of the Polity V variables, they are considered similarly to GDP as both the level of the democracy and autocracy measure, as well as the difference in the democracy and autocracy measure of an edge. An additional statistic included is the number of geometrically-weighted edgewise shared partners. This is a measure to model triad closure, related to transitivity shown in Table 1, where an edgewise shared partner is a node that completes a triangle and is either the edge $a \leftarrow c$ or the one $a \rightarrow c$ from Table 1, depending on the specification being in- or out (Hunter 2007).

Table 2: Variables of the model

Term	Variable	Description
Edges	g_{edges}	Sum of edges
Mutuality	g_{mutual}	Sum of mutual edges
Balance	g_{balance}	Sum of balanced edges
Transitivity	g_{transit}	Sum of transitive edges
GDP	$g_{\text{log distw}}$ $g_{\text{diff GDP}}$	$\log \text{GDP}$ $\lvert \text{GDP}_i - \text{GDP}_j \rvert$
Weighted Distance	g_{distw}	Length of distance between economic centers
Language	g_{lang}	Binary common language
Contiguity	g_{contig}	Binary contiguity
RTA	g_{rta}	Binary presence of RTA
Political Distance (UN votes)	$g_{\text{UN vote}}$	Distance between ideal points (IPD)
Political Distance (Polity)	g_{democ} $g_{\text{diff democ}}$ g_{autoc} $g_{\text{diff autoc}}$	Democracy score (democ) $\lvert \text{democ}_i - \text{democ}_j \rvert$ Autocracy score (autoc) $\lvert \text{autoc}_i - \text{autoc}_j \rvert$
Edgewise Shared Partner	$g_{\text{esp in}}$ $g_{\text{esp in}}$	Completing triangles

The terms of the model are presented again in Table 2 along with their variables g_m as network statistics of the set of networks over all time periods. Combining these into an additive model that is the function of network characteristics introduced in the discussion of (T)ERGMs that determines the probability of the observed network. For the first source of political distance data, the distance between the ideal points in UN GA voting behavior, the model is defined as follows:

$$\Gamma_{\text{UN vote}} = \theta_1 g_{\text{edges}} + \theta_2 g_{\text{mutual}} + \theta_3 g_{\text{balance}} + \theta_4 g_{\text{transit}} + \theta_5 g_{\log\text{GDP}}$$
$$+\theta_6 g_{\text{diff GDP}} + \theta_7 g_{\text{distw}} + \theta_8 g_{\text{lang}} + \theta_9 g_{\text{contig}} + \theta_{10} g_{\text{rta}} + \theta_{11} g_{\text{UN vote}} + \theta_{12} g_{\text{esp in}} + \theta_{13} g_{\text{esp out}}$$

The first four terms relate directly to the network itself, with the edges term being related to the intercept in regression models. For the second data source of political distance, the variables from the Polity V dataset, the model is altered to include them in the two ways described above. The model then reads as:

$$\Gamma_{\text{Polity}} = \theta_1 g_{\text{edges}} + \theta_2 g_{\text{mutual}} + \theta_3 g_{\text{balance}} + \theta_4 g_{\text{transit}} + \theta_5 g_{\log\text{GDP}} + \theta_6 g_{\text{diff GDP}}$$
$$+\theta_7 g_{\text{distw}} + \theta_8 g_{\text{lang}} + \theta_9 g_{\text{contig}} + \theta_{10} g_{\text{rta}}$$
$$+\theta_{11} g_{\text{democ}} + \theta_{12} g_{\text{diff democ}} + \theta_{13} g_{\text{autoc}} + \theta_{14} g_{\text{diff autoc}} + \theta_{15} g_{\text{esp in}} + \theta_{16} g_{\text{esp out}}$$

3.6 Estimation

The estimation of the model presented is carried out using statistical packages developed for (T)ERGMs. The implementation of network analysis used for this is the package `statnet` developed by Pavel N. Krivitsky et al. (2003-2020) for the statistical software `R` (R Core Team 2020). It is used to transform the data that is collected in the form of dyad-observations into network objects that can be used to estimate the (T)ERGMs. These are, in turn, estimated using the `btergm` package by Leifeld, Cranmer, and Desmarais (2018) that was developed for the time- and resource-preserving implementation of the usually very computing-intensive estimation of TERGMs. In order to do so, it takes advantage of the properties of MPLE in the context of TERGMs which allow for bootstrapping the estimator, thereby reducing the resources necessary for the estimation of the model (see above). In order for the MPLE to be consistent and converge to the true estimator, a sufficiently high number of nodes or time steps is necessary. Thus, with the inclusion of a sufficiently long time-horizon, the usage of the "shortcut" of MPLE can be utilized to soften the computational load, with Leifeld, Cranmer, and Desmarais (2018) quoting 20 to 50 time slices as used in international relations literature as adequate for favoring the MPLE over the more time-consuming Markov Chain Monte Carlo Maximum Likelihood Estimator (MCMC-MLE). In the models presented herein, the number of nodes is consistently very large, as well as spanning a time-horizon that is within the range of recommended intervals (see the description of the data). A drawback of the estimation using the `btergm` package, as with other implementations of (T)ERGMs, is the current lack of implementation for estimation of models of valued networks. This can be attributed to the relative novelty of the utilization of (T)ERGMs in network analysis of quantitative variables, as in network analysis ties are often binary, and thus only the probability of the presence of an edge in the realized network is of interest, whereas the magnitude is either conceptually nonexistent, as in the case of, e.g., friendship networks (a popular example of network analysis (Pavel N. Krivitsky et al. 2003-2020)), or only of minor relevance. Due to the increased usage of (T)ERGMs also for quantitative networks, the implementation of the theory for valued (T)ERGMs (Bruce A. Desmarais and Cranmer 2012) is envisaged, but currently not implemented. The model presented above is therefore estimated as a binary one, making it similar to a logit model, with estimators indicating the probability of the presence of a tie, rather than its magnitude.

Another difficulty of the ITN in relation to network analysis is the ubiquity of trade relations between countries. As virtually all countries are connected to each other through trade ties, the ITN is close to a complete network, where every node is connected to every other node. In temporal network analysis, variation both between time periods and actors is, however, required in order to arrive at meaningful estimator, much alike to other ways of statistical inference. In order to estimate models of the ITN where some variance is present in the data, different approaches can be employed. On the one hand, it is possible to focus on (sub)industries, estimating a model for a specific fragment of world trade rather the whole (for an example see Herman 2021). On the other hand, a threshold can be set in order to exclude any trade relation that does not reach this threshold, artificially setting it equal to 0 and thus creating a less complete network than the one observed (for this approach see M. P. Smith 2016). The first approach seems insufficient for the study of political influence on trade, as industries where enough variation is present in trade relations tend to be heavily politicized ex-ante, apparent from the common focus on the arms-industry (examples are Herman 2021; and Lebacher, Thurner, and Kauermann 2021). As outlined above, the consideration of security issues can be particularly strong in sectors where externalities to a state's security from trade are high, as in the case of arms trade (Haim 2016). Therefore, all sectors are included in the estimation and a threshold is chosen, below which a trade relationship is treated as zero. In order to additionally account for sectoral variation, this threshold is applied to the trade per sector as classified by the Harmonized System (HS) nomenclature. In order to not skew the network towards large countries, the trade relationship is included for both countries when it reaches the threshold for only one partner. The MPLE is then estimated with this formatted data using 1000 replications of the bootstrapping procedure. The number of countries included depends on the variable of consideration. In the case of the UN vote correlation it is 152 countries where data is available for all time periods from 1995 to 2019 and in the case of the Polity variables it is 56 countries with data until 2018[8].

[8]Note that while the smaller sample may cause concern, it is in line with other studies, being almost identical to the sample used by Herman (2021) and includes almost all major states.

4 Results

The results from the estimation of the model are presented in Table 4. The table gives the log-odds L for each variable, which can be translated into a probability p according to the formula $p = \frac{\exp L}{1+\exp L}$. First, the direction of the estimated effects is of interest. Table 3 gives the direction of the effect where statistically significantly different from zero, allowing for comparison between the two models, as well as comparing them to the ERGM model by Herman (2021)[9]. The directions are relatively consistent across both specifications of the model and the benchmark from the literature. They also align with the results from the gravity literature where the terms estimated are compatible.

Table 3: Comparison of the effect directions

Term	UN vote correlation	Polity variables	Herman (2021)
Edges	-	-	-
Reciprocity	+/-	+/-	+/-
GDP	+	+	+
Weighted Distance	-	-	-
Language	+	+	+(/-)
Contiguity	+	-	+
RTA	+	0	+
Edgewise Shared Partner	-	+	+

The results show high significance for almost all covariates across both models. The intercept-like edges term has a relatively large negative magnitude, which can be

[9]Where the direction differs across the different samples that he uses to estimate ERGMs all directions are given.

conceived as the trade costs that are present even before the inclusion of other variables like distance. The mutuality is negative in both model specifications with a similar magnitude, indicating that a trade relation in one direction between a pair of countries makes counter trade less likely, going against expectations. This can, however, be viewed in conjunction with the other two network terms indicating reciprocity, balance and transitivity, which are positive in both models, even though differing in magnitude between the two models and being below the magnitude of the mutuality term. When assuming an intricate structure of trade in a relatively complete network, the likelihood of an edge being mutual but not transitive and/or balancing a triad can be assumed to be lower. Another explanation would be a division in exporters and importers between countries, where mutual trade is less likely. The two GDP terms both show the expected positive effect, indicating that a higher GDP leads to a likelier trade relationship simply due to size. The difference in GDP shows that there is not a grouping of small and big countries in trade, but rather the dominance of big countries that attract trade, one central aspect of the gravity theory. A shared language increases the likelihood of an edge between a pair of nodes, as common understanding lowers trade costs and facilitates trade between countries. The effect of contiguity differs across the two models, having a positive effect using UN vote correlations and a negative ones in the one with Polity V variables. A possible explanation would be that the effect differs with democratic and autocratic countries, so that when taking this explicitly into account contiguity becomes a hindrance in fact, relating to the security externalities mentioned by Haim (2016). The effect of RTAs is again positive in the UN vote correlation model but has no statistically significant effect in the model with Polity V variables. This could again be explained by the difference between democratic and autocratic countries, similar to the argument by Gibler and Wolford (2006) that democratic countries have a lesser need for alliances that was empirically shown to influence trade by Cranmer, Desmarais, and Menninga (2012). While the model with Polity V variables differs in some aspects, the social selection attributes that were included based on their demonstrated relevance from the gravity literature are largely confirmed also by the network model (cf. Herman 2021). Jumping to the edgewise shared partner term, there is again a difference between the two models. A positive estimate can be interpreted as the inclination to trade if countries share a trading partner that is a third-country, with some nodes serving as central "hubs" of either import or export, incoming or outgoing. The first model with UN vote correlations unexpectedly estimates a negative edgewise shared partner term, whereas the model with the Polity V variables shows the expected direction of the term, with a shared partner being conducive to trade.

Table 4: TERGM results

	Political distance variable	
	UN vote correlation	Polity V distance
	(1)	(2)
Edges	−3.948***	−3.915***
	(0.073)	(0.163)
Mutual	−0.809***	−1.323***
	(0.053)	(0.056)
Balance	0.010***	0.042***
	(0.001)	(0.003)
Transitive	0.021***	0.051***
	(0.0004)	(0.002)
log(GDP)	0.071***	0.076***
	(0.005)	(0.008)
Difference GDP	0.150***	0.061***
	(0.003)	(0.007)
Weighted Distance	−0.0001***	−0.0001***
	(0.00000)	(0.00000)
Language	0.347***	0.138***
	(0.010)	(0.024)
Contiguity	0.121***	−0.313***
	(0.022)	(0.050)
RTA	0.404***	−0.016
	(0.029)	(0.038)
Political Distance	−0.024**	
	(0.013)	
Democracy		0.027***
		(0.004)
Democracy Difference		0.018***
		(0.005)
Autocracy		0.006
		(0.007)
Autocracy Difference		−0.006
		(0.007)
Incoming Shared Partner	−0.016***	0.019*
	(0.005)	(0.010)
Outgoing Shared Partner	−0.021***	0.014**
	(0.004)	(0.007)

*p<0.1; **p<0.05; ***p<0.01

Turning to the influence of political distance on trade, both models show the expected impact. First, the UN vote correlation model estimates a negative coefficient for the effect of the distance between ideal points on trade, where a greater distance is related to a lower probability of an edge between the two nodes. This is the expected direction and also aligns with earlier work by Umana Dajud (2013). Turning to the Polity V variables, a more differentiated picture arises. While the two inclusions of the democracy measure, both the level and the absolute difference, have a significant positive effect, the autocracy measures are not statistically significantly different from zero. This is in alignment with the literature on democratization and trade, which has shown that the driving force of increased trade is democratization, decidedly after 1990 (Decker and Lim 2009). The results suggest a statistically significant relationship between political distance and international trade in both models, with the Polity V variables adding insight into the importance of the democratic closeness in the network, with the autocratic component not statistically significant.

4.1 Robustness

In order to substantiate the results from above, the trade-offs described in the estimation are tested for robustness. To do so, the two ways in which the data was restricted to allow for variance to utilize in the model are changed. First, the threshold that is used to reduce the number of trade ties is varied. in both directions. While a higher threshold leads to the exclusion of more trade ties that are present in the realized network, it also allows for more variance which strengthens the results from the model. The threshold is varied upwards in two steps to 10% and 20%. In order to confirm that the threshold does not dismiss too many trade ties present in the realized network, it is also varied downwards to 1%, in order to confirm that the higher number of ties does not invalidate any of the results. The TERGM output is presented in Tables 5 and 6.

In addition, the decision to apply the threshold at the HS2 level to the data is also tested. As there are several levels of granularity to the HS data, with a 6 digit, 4 digit and the used 2 digit code, applying the threshold at the different levels can lead to the exclusion of a sub-industry at a level of lower granularity that is particularly important, but does not have adequate weight at a lower level of granularity in order to not be excluded by applying the threshold at that level. Therefore, both models are re-estimated with the threshold applied at the HS4 and HS6 level of the data, leading to a higher granularity of the included ties. These re-estimated results are presented in Tables 7 and 8 They show similar results in magnitude and statistical significance for the topological and social selection attributes. Importantly, however, the political distance gives a more varied picture in these models, changing sign in the case of the UN vote correlation, suggesting that at a more granular industry level, and thus for more specialized countries, there is a stronger inclusion in the network of international trade with politically distant countries. This is further substantiated with the results of the model with the Polity V variables, where the variables related to the democratic scale stay statistically significant and positively related to the likelihood of trade ties, while the variables based on the autocratic scale also become significant at more granular levels with a negative relationship for the difference and positive for the level. These results suggest further that the inclusion of countries into the ITN can be motivated by the desire to bind also politically distant countries to the international order through trade relationships.

In order to confirm that the bootstrapping procedure employed in the estimation of the models, used to ease the computational burden and make estimation possible, does indeed give a true estimate, the standard error of the TERGMs need to be normally distributed. As the MPLE converges to the MCMC-MLE only for high enough t and n, such a test is necessary in order to validate that the chosen estimation technique gives an accurate estimator. As B. A. Desmarais and Cranmer (2012) note, in order to arrive at consistent bootstrapped confidence interval the MPLE has to be consistent and normally distributed, which they confirm by employing Monte Carlo studies to validate the bootstrapping technique. The quantile-quantile plots with the normal distribution from the bootstrapped estimations of the TERGMs for UN vote correlation and the Polity variables are presented in Figure 1. They confirm the assumption of normally distributed standard errors underlying the estimation technique using the MPLE with bootstrapped confidence interval. In addition, quantile-quantile plots for the additional estimations presented above as robustness tests are shown in the appendix in Figures 2 and 3. They all show that the MPLE is a valid estimation technique for the TERGMs.

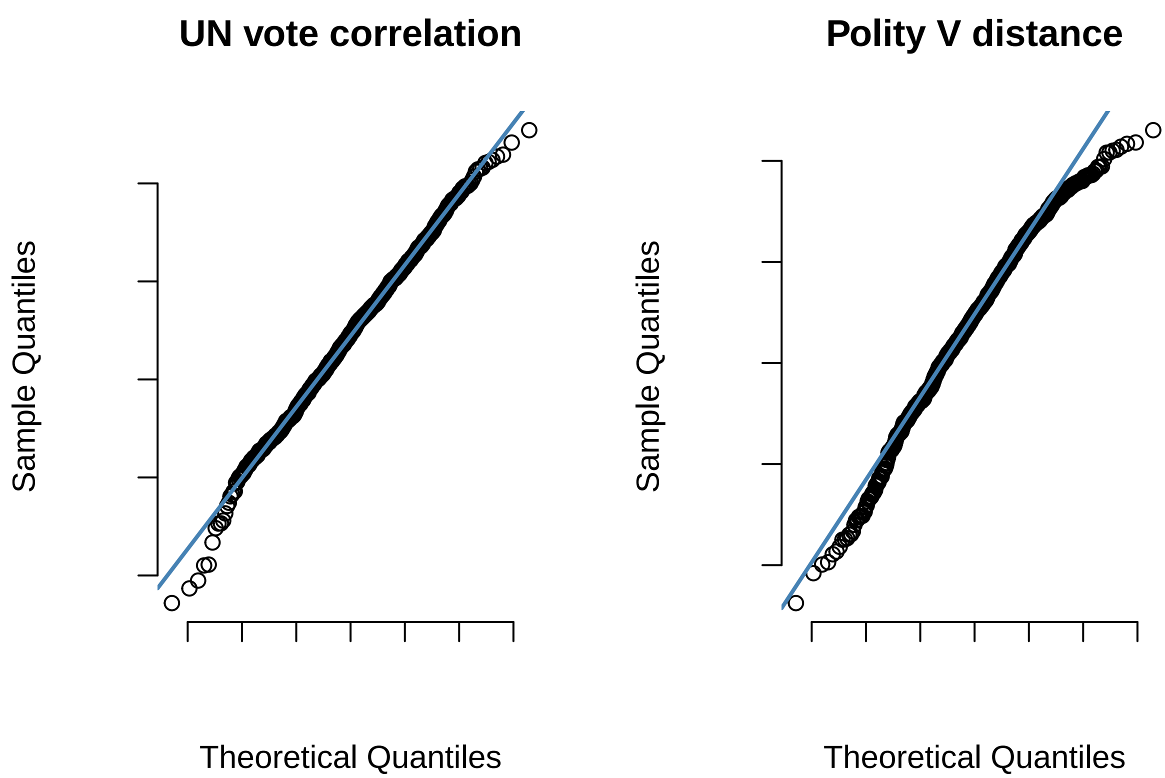

Figure 1: Quantile-Quantile Plots

5 Interpretation

The results confirm a statistically significant relationship between political distance and the likelihood of a trade tie. What the robustness tests show in addition, is that the granularity of the trade tie, i.e., whether a general industry or narrower sub-industries are considered, has a differing effect on that likelihood. While at a low granularity trade is more likely with politically close partners, this effect reverses for higher granularities. While at a general industry level politically close states are likelier to trade with each other, for more specific sub-industries it is in fact likelier for an ideologically distant state to be tied to the network of international trade. To make sense of this pattern, there are two possible explanations. On the one hand, this could be due to specialization of countries, where a specific sub-industry is dominated by a state that thus becomes a central actor within the ITN. In order for the observed effect to occur, this would need a relationship between sub-industrial dominance and autocracy, which, while possible for some specific sub-industries, is disregarded as an explanation due to the lack of broad applicability across several different such sub-industries. On the other hand, the differing effect can be explained when turning to international relations theory of networks between states. As a framework, I turn to the theory of weaponized interdependence advanced by Farrell and Newman (2019). The theory states that nations hold a unique *pouvoir* (in the vocabulary of Hans Morgenthau (cf. Rösch 2014)) based on their position in the network of international trade. They are able to weaponize their trade ties in the interdependent network that arises from international trade. This effect is naturally stronger the more trade ties a state has and thus the more central its position in the ITN. Binding also ideologically distant states into a state's network of trade ties allows that state to more effectively make use of the *pouvoir* afforded to it by weaponized interdependence and thus gives it a stronger position in international politics. As it is far likelier to dominate in a narrower sub-industry compared to a less granular industry and also sufficient to exploit interdependence, the effect would be expected to show at higher levels of granularity in the analysis.

The results from the TERGM using the UN vote correlation as dependent variable give evidence that suggests weaponized interdependence is occurring, where the sign of political distance changes when going up in granularity. While at low levels of granularity there can be observed a higher likelihood of trade ties between ideologically close states, where the desire to group with politically similar states overweighs, for higher levels of granularity, politically distant states are bound through trade ties, i.e., the likelihood of a trade tie between them is higher, which allows a state to weaponize its interdependence, which, given the nature as a form of *pouvoir*, it likelier exerts over ideologically distant states. As weaponized interdependence is characterized through dominance in a sub-industry due to the increased likelihood of such a position, the increase in magnitude when going up in granularity gives further support for this thesis. The results form the TERGM with the Polity V dependent variables gives some evidence on the possible direction of weaponized interdependence occurring. Note that for levels of granularity where the two autocracy variables become significant, the sign of the difference variable differs between its democracy and autocracy variant. While the absolute difference in the democracy scale has a positive sign, the absolute difference in the autocracy scale has a negative sign. This suggests that the effect of weaponized interdependence suggested from the results of the UN vote TERGMs occurs between countries distant on the democracy scale and close on the autocracy one. The configuration this entails is a pair of countries where one is high and the other low on the democracy scale, with little distance between them on the autocracy scale, for example both at a low or middle level. Weaponized interdependence thus seems to be used more strongly by democratic state, which on the one hand cluster together as evidenced by the positive sign of the absolute level of the democracy, and on the other hand bind states that are ideologically distant, albeit not strongly autocratic, to themselves and more widely the “liberal international order”. Autocratic states, on the other hand, also cluster together, yet do so only at higher granularity, and are not able to bind ideologically distant other states to themselves. The support for weaponized interdependence from this study thus points to a solidifying of the liberal international order dominated by states classified as high on the Polity V democracy scale, which in addition to grouping between them also exert influence over other, politically and ideologically distant states. The *pouvoir* of weaponized interdependence is one that is chiefly centered on democratic states dominating the international order and trade in the first place and giving them an additional mechanism to exert influence.

6 Conclusion

The study of international trade has been primarily conducted in the setting of gravity models that take into account economic and cultural variables as possible determinants. The reality of international trade, however, is on the one hand marked by a network structure between countries as the set of nodes of an intricate network of world trade, the ITN. Additionally, trade is not determined solely by economics and culture, but, on the other hand, dependent on the political environment and hence on the political distance as much as the cultural and physical distance between countries as another part of trade costs. This work has synthesized findings by Umana Dajud (2013) and Herman (2021), as well as expanded the analysis, by conducting network inference over time taking into account the political distance. This was achieved using TERGMs as statistical tool, which has seen a recent heightened interest in political science, but not yet in economics, albeit its suitability for the question raised in this paper, namely whether trade is influenced by the political distance between states Using TERGMs as models to analyze the international trade network allows for deeper insights into higher-order dependencies. The investigation has found the expected effect. Greater political distance, as measured by the distance between ideal points of voting in the UN General Assembly, has a negative effect on the likelihood of a trade tie. Additional light is shed on this relation by the inclusion of the democracy and autocracy from the Polity V dataset. Here, the analysis shows that the effect of political distance on trade stems from the democratic level and difference thereof to other nodes, with stronger democracy having a positive impact on trade. The autocratic scale of the dataset on the other hand has no statistically significant impact. This is in line with the literature finding that the rapid democratization at the end of the 20th century went hand in hand with an increase in trade activity. These results are robust to a number of changes in the specification, varying the choice taken in the construction of the network investigated. The model further finds that the effect of network relations varies, with solely a mutual relationship not raising the likelihood of a trade tie, but rather completing triangles and grouping being significant instigators to trade in a network context. Viewed in conjunction with the results on political difference, this further suggests that countries high on the democratic scale group in strong trade networks. While this result on a level of low granularity is in line with previous literature, the study has also produced novel insight into the trade network. Looking at a more granular industry level, the results for the autocratic scale become significant for trade ties that are included when considering more specialized states, results that are aligned with the weaponized interdependence thesis of Farrell and Newman (2019), where countries are bound into networks to the international order. Democratic countries trade among each other, but also with less democratic but not (much) more autocratic states, giving evidence for the structure that allows for the effect of weaponized interdependence among democratic countries, however not so among autocratic countries.

The results show the importance of politics as well as political and ideological distance between countries in international trade. The international trade network is not only formed by economic and cultural factors, but also shaped by the politics of its actors, the countries on the international plane. Their position in this network of international trade is shaped by their ideological distance to each other, with trade being determined by political distance.

7 References

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8 Appendix

Additional Q-Q plots

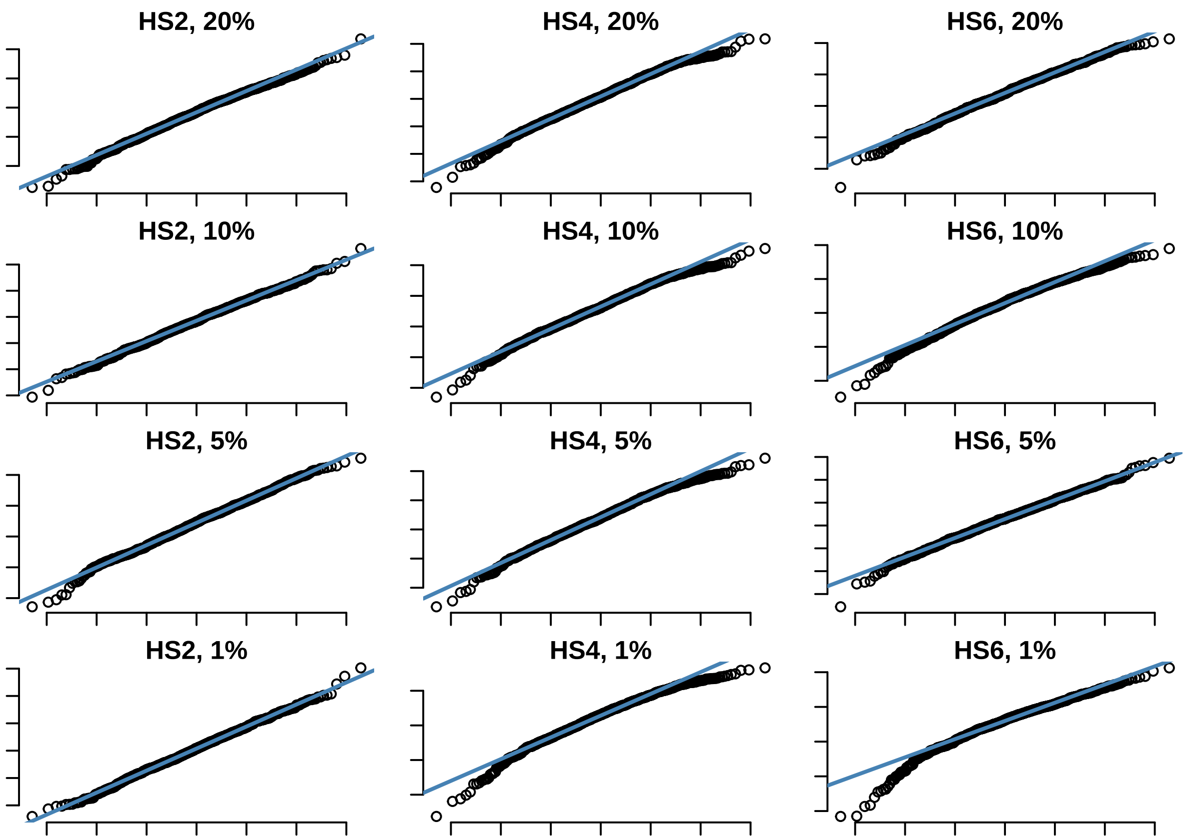

Figure 2: Additional Quantile-Quantile Plots for UN Vote Correlation

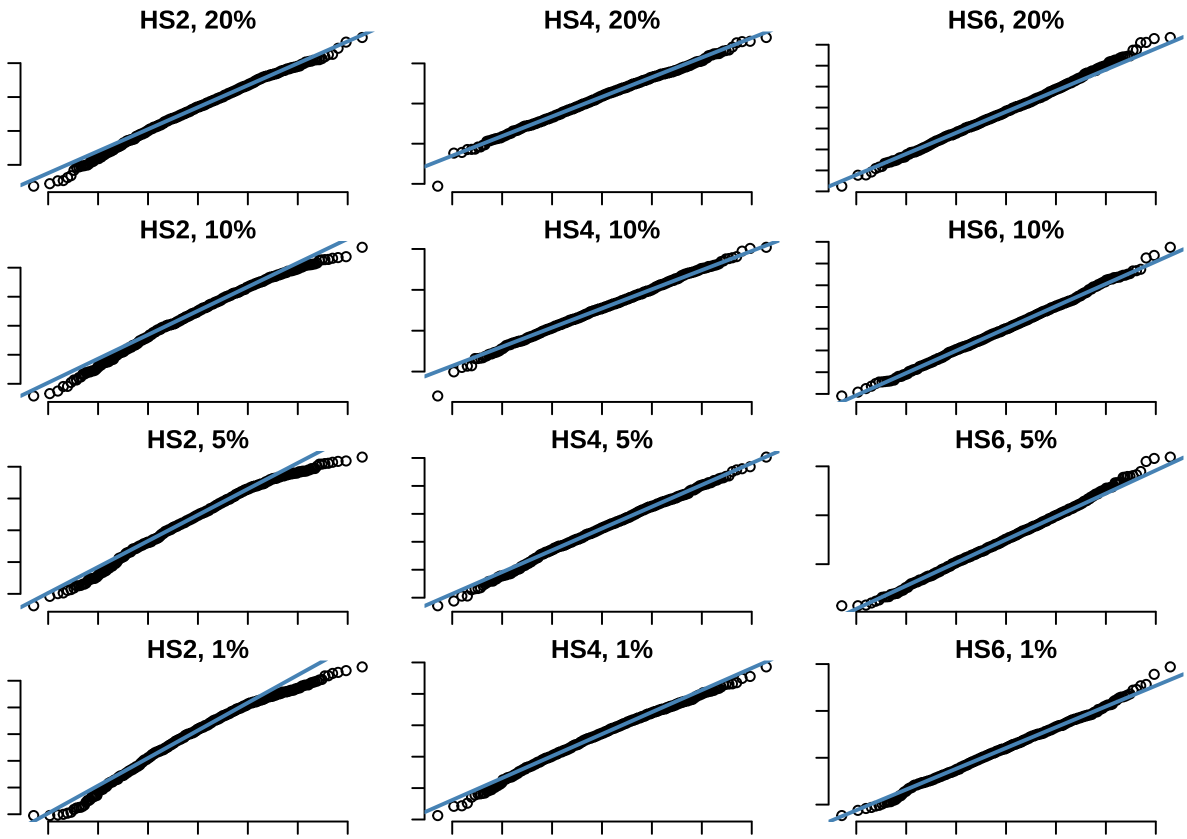

Figure 3: Additional Quantile-Quantile Plots for Polity V variables

Additional TERGM results

Table 5: Additional TERGM results: Varying Threshold (UN Vote)

	UN vote correlation			
	Trade exclusion cutoff			
	20%	10%	5%	1%
	(1)	(2)	(3)	(4)
Edges	−4.516***	−4.113***	−3.948***	−4.081***
	(0.073)	(0.079)	(0.073)	(0.081)
Mutual	−1.392***	−1.016***	−0.809***	−0.542***
	(0.045)	(0.045)	(0.053)	(0.077)
Balance	0.020***	0.014***	0.010***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Transitive	0.026***	0.023***	0.021***	0.018***
	(0.0005)	(0.001)	(0.0004)	(0.001)
log(GDP)	0.100***	0.082***	0.071***	0.074***
	(0.003)	(0.004)	(0.005)	(0.007)
Difference GDP	0.198***	0.177***	0.150***	0.113***
	(0.004)	(0.003)	(0.003)	(0.004)
Weighted Distance	−0.0001***	−0.0001***	−0.0001***	−0.0001***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Language	0.386***	0.374***	0.347***	0.285***
	(0.007)	(0.008)	(0.010)	(0.010)
Contiguity	0.594***	0.370***	0.121***	−0.213***
	(0.022)	(0.019)	(0.022)	(0.032)
RTA	0.369***	0.389***	0.404***	0.415***
	(0.016)	(0.022)	(0.029)	(0.035)
Political Distance	0.032***	−0.003	−0.024**	−0.003
	(0.008)	(0.011)	(0.013)	(0.015)
Incoming Shared Partner	−0.003	0.004	−0.016***	−0.011**
	(0.005)	(0.007)	(0.005)	(0.005)
Outgoing Shared Partner	0.029***	0.017***	−0.021***	−0.053***
	(0.004)	(0.003)	(0.004)	(0.008)

*p<0.1; **p<0.05; ***p<0.01

Table 6: Additional TERGM results: Varying Threshold (Polity)

	Polity V distance			
	Trade exclusion cutoff			
	20%	10%	5%	1%
	(1)	(2)	(3)	(4)
Edges	-4.267^{***}	-4.114^{***}	-3.915^{***}	-3.574^{***}
	(0.136)	(0.170)	(0.163)	(0.199)
Mutual	-1.276^{***}	-1.346^{***}	-1.323^{***}	-1.239^{***}
	(0.080)	(0.072)	(0.056)	(0.071)
Balance	0.042^{***}	0.044^{***}	0.042^{***}	0.035^{***}
	(0.003)	(0.003)	(0.003)	(0.004)
Transitive	0.051^{***}	0.050^{***}	0.051^{***}	0.055^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
log(GDP)	0.101^{***}	0.093^{***}	0.076^{***}	0.047^{***}
	(0.006)	(0.007)	(0.008)	(0.011)
Difference GDP	0.097^{***}	0.081^{***}	0.061^{***}	0.018^{**}
	(0.006)	(0.007)	(0.007)	(0.007)
Weighted Distance	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Language	0.276^{***}	0.204^{***}	0.138^{***}	0.046^{*}
	(0.020)	(0.021)	(0.024)	(0.025)
Contiguity	-0.036	-0.216^{***}	-0.313^{***}	-0.555^{***}
	(0.040)	(0.041)	(0.050)	(0.067)
RTA	0.096^{***}	0.026	-0.016	-0.093
	(0.031)	(0.031)	(0.038)	(0.054)
Democracy	0.027^{***}	0.027^{***}	0.027^{***}	0.021^{***}
	(0.003)	(0.004)	(0.004)	(0.005)
Democracy Difference	0.021^{***}	0.018^{***}	0.018^{***}	0.013^{**}
	(0.005)	(0.005)	(0.005)	(0.006)
Autocracy	0.003	0.002	0.006	-0.0002
	(0.006)	(0.007)	(0.007)	(0.006)
Autocracy Difference	-0.010	-0.005	-0.006	0.005
	(0.007)	(0.007)	(0.007)	(0.007)
Incoming Shared Partner	-0.023^{*}	0.013	0.019^{*}	0.043^{***}
	(0.013)	(0.010)	(0.010)	(0.007)
Outgoing Shared Partner	0.006	0.002	0.014^{**}	0.018^{***}
	(0.012)	(0.009)	(0.007)	(0.006)

*p<0.1; **p<0.05; ***p<0.01

Table 7: Additional TERGM results: Varying Industry Classification (UN Vote)

	UN vote correlation		
	HS classification		
	HS2	HS4	HS6
	(1)	(2)	(3)
Edges	−3.948***	−2.930***	−2.967***
	(0.073)	(0.154)	(0.084)
Mutual	−0.809***	−2.600***	−2.757***
	(0.053)	(0.080)	(0.028)
Balance	0.010***	0.056***	0.054***
	(0.001)	(0.001)	(0.002)
Transitive	0.021***	0.038***	0.039***
	(0.0004)	(0.001)	(0.001)
log(GDP)	0.071***	−0.008	−0.004
	(0.005)	(0.011)	(0.006)
Difference GDP	0.150***	0.176***	0.274***
	(0.003)	(0.004)	(0.004)
Weighted Distance	−0.0001***	−0.00001***	−0.00000**
	(0.00000)	(0.00000)	(0.00000)
Language	0.347***	−0.061***	−0.185***
	(0.010)	(0.007)	(0.017)
Contiguity	0.121***	−0.914***	−0.775***
	(0.022)	(0.032)	(0.045)
RTA	0.404***	−0.381***	−0.431***
	(0.029)	(0.016)	(0.025)
Political Distance	−0.024**	0.109***	0.213***
	(0.013)	(0.014)	(0.008)
Incoming Shared Partner	−0.016***	0.006	−0.076***
	(0.005)	(0.007)	(0.010)
Outgoing Shared Partner	−0.021***	0.012***	−0.058***
	(0.004)	(0.003)	(0.009)

*p<0.1; **p<0.05; ***p<0.01

Table 8: Additional TERGM results: Varying Industry Classification (Polity)

	Polity V distance		
	HS classification		
	HS2	HS4	HS6
	(1)	(2)	(3)
Edges	−3.915***	−2.307***	−2.275***
	(0.163)	(0.159)	(0.247)
Mutual	−1.323***	−2.338***	−2.076***
	(0.056)	(0.068)	(0.109)
Balance	0.042***	0.129***	0.064***
	(0.003)	(0.005)	(0.008)
Transitive	0.051***	0.104***	0.140***
	(0.002)	(0.002)	(0.003)
log(GDP)	0.076***	−0.029***	−0.022***
	(0.008)	(0.008)	(0.006)
Difference GDP	0.061***	0.233***	0.346***
	(0.007)	(0.008)	(0.008)
Weighted Distance	−0.0001***	0.00002***	0.00001***
	(0.00000)	(0.00000)	(0.00000)
Language	0.138***	−0.197***	−0.170***
	(0.024)	(0.040)	(0.052)
Contiguity	−0.313***	−0.717***	−0.461***
	(0.050)	(0.059)	(0.055)
RTA	−0.016	−0.424***	−0.443***
	(0.038)	(0.041)	(0.056)
Democracy	0.027***	0.016***	0.020***
	(0.004)	(0.004)	(0.005)
Democracy Difference	0.018***	0.038***	0.048***
	(0.005)	(0.005)	(0.005)
Autocracy	0.006	0.026***	0.031***
	(0.007)	(0.007)	(0.005)
Autocracy Difference	−0.006	−0.019***	−0.023***
	(0.007)	(0.007)	(0.006)
Incoming Shared Partner	0.019*	−0.168***	−0.269***
	(0.010)	(0.011)	(0.016)
Outgoing Shared Partner	0.014**	−0.101***	−0.226***
	(0.007)	(0.009)	(0.008)

*p<0.1; **p<0.05; ***p<0.01