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Agencies without borders: Explaining partner selection in the formation of transnational agreements between regulators

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Abstract

Transnational collaboration between regulatory agencies has proliferated rapidly within the last three decades. However, given that information regarding the motives, trustworthiness, and capabilities of potential partners is typically imperfect, decisions about with whom to collaborate are inevitably characterized by a degree of uncertainty. To better capture these dynamics, this article uses a network analytical perspective and hypothesizes that agencies are more likely to form agreements with agencies to whom they are already indirectly connected (transitivity), that are highly connected (preferential attachment), or with whom they share tie-characteristics (assortativity). To test these hypotheses, a stochastic actor-oriented model is used to analyze an original, self-coded data set in which bilateral information exchange agreements between national securities agencies (n = 143) are mapped out over a 18-year period. The results show that the formation of agreements between regulatory agencies is driven by (i) the number of shared partners (i.e. triadic closure); and (ii) similarity regarding agency characteristics (i.e. homophily).

Keywords: enforcement cooperation, network analysis, partner selection, regulatory networks, transnational agreements.

1. Introduction

Transnational collaboration between regulatory agencies has proliferated rapidly within the last three decades. The internationalization of markets and the need to cope with transnational policy issues has facilitated the development of regulatory networks in diverse policy areas, such as energy, telecommunications, privacy protection, human rights, international competition, and financial markets regulation (see Slaughter 2004; Bach *et al.* 2016). In these networks, agencies collaborate within multilateral settings, but are also connected through forms of bilateral collaboration, creating complex webs of information exchange agreements, partnerships, and memoranda of understanding (MOUs). These agreements institutionalize channels of regulatory cooperation between agencies and are often seen as a means to reduce the transaction costs involved in the exchange of sensitive regulatory information (Lazer 2001; Trachtman 2007). In that sense, they have a clear functional purpose, helping regulatory agencies to remedy shared problems in their common environments, such as the need to effectively regulate cross-market activity or conduct cross-border criminal/regulatory investigations.

However, such a functional perspective to transnational cooperation merely provides an explanation for the proliferation of bilateral agreements between agencies in general; the specific decisions of regulatory agencies about *with whom* to form bilateral agreements still warrants closer scrutiny. Given that these agreements typically involve the exchange of sensitive information regarding ongoing legal investigations or in-house evaluations, agencies need to carefully select their partners to avoid leaks that compromise internal investigations or reveal sensitive information (Efrat & Newman 2018). But because information regarding the motives, trustworthiness, and capabilities of potential partners is typically imperfect, such decisions are inevitably characterized by a degree of uncertainty. For instance, foreign agencies may have different professional standards regarding the handling of confidential/privacy-sensitive information, such as taxpayer-specific information in the case of tax authorities or business secrets in the case of antitrust

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regulators (see Yang & Maxwell 2011). Or exchanged information might be misused for other purposes than intended, such as the persecution of political opponents (see Nadelmann 1993).

Risks for defection and vulnerability to opportunistic behavior thus characterize transnational agreement formation between regulators, and potentially weigh in on an agency's decisionmaking about with whom to form such agreements (cf. Feiock *et al.* 2012). To better capture this underlying uncertainty, this article takes a network analytical perspective, which explicitly conceptualizes the existing network of relationships as an information repository through which organizations can reduce uncertainty about the trustworthiness of potential partners and learn about opportunities for new ties (see Gulati & Gargiulo 1999; Feiock & Scholz 2010). For instance, scholars have noted how past ties and third-party actors help agencies to mitigate risks of interagency cooperation by providing endorsements about or referrals to potential partners (Ahuja 2000; Carpenter *et al.* 2004). Moreover, the formation of information exchange agreements can serve as signals of enhanced legitimacy for regulatory agencies and their respective jurisdictions (Ostrom 1990; Baum & Oliver 1991). The information provided by existing network relationships thus offers important cues for agencies about with whom to engage in future relationships (Gulati & Gargiulo 1999; Lee *et al.* 2012).

Based on these insights, this article assumes that the formation of new bilateral agreements is embedded by a broader structure of already existing agreements, potentially increasing the probabilities of agreements between agencies from some countries and decreasing the probabilities of such agreements between others. Theoretically, this means that the existing transnational network of regulatory agencies is defined as a strategic environment in which agencies bargain over new agreements, endogenously influencing the way in which future agreements are formed (cf. Gulati & Gargiulo 1999). From this, the analysis assesses whether agencies are more likely to form agreements with agencies to whom they are already indirectly connected (i.e. network transitivity), agencies they perceive as popular or high status (i.e. preferential attachment), or with agencies with whom they share network attributes (i.e. structural homophily). Testing hypotheses related to these basic network effects allows for conclusions about the process of network evolution and the (theoretical) mechanisms driving it. Although scholars have frequently noted similar kinds of network dynamics in processes of policy diffusion or standard adoption (e.g. Simmons *et al.* 2006), how these dynamics matter for the evolution of information exchange agreements and enforcement cooperation is still unclear (see Efrat & Newman 2018).

Theoretically, such a network analytical approach to transnational regulatory networks helps to clarify the role that the specific structure of relationship between agencies is likely to play in how these networks form and develop. This is an important addition to the literature that has primarily conceptualized such networks in metaphorical terms (Slaughter 2004; Mastenbroek & Sindbjerg Martinsen 2018, see also Vantagiatto 2018), or has analytically ignored such structural network patterns and relational interdependence by only focusing on domestic (Bach & Newman 2014) or sectoral (Van Boetzelaer & Princen 2012) factors for explaining transnational collaboration and coordination. Moreover, while many of these studies focus on decisions of agencies to join "a network," the theoretically more interesting question lies in considering which specific partners agencies choose within these networks. Rather than loosely analogizing about the development of network forms of collaboration, network models thus give our intuitions regarding transnational forms of collaboration a more precise theoretical formulation (see Hafner-Burton *et al.* 2009; Kinne 2013). This gives a better understanding of globalizing administrative patterns and the underlying network dynamics that potentially play a role in how they develop. Particularly given the increasing prevalence of these transnational agreements in various regulatory sectors (Efrat & Newman 2018), this article provides a basis of further theorizing about future developments.

In terms of practical relevance, the way in which information exchange agreements form and develop is also important to consider. Given internationalized markets, national citizens have increased opportunities to be defrauded abroad and national firms can more easily engage in misconduct beyond what national agencies can meaningfully scrutinize (Cadmus 2010). Information exchange agreements and memoranda on enforcement cooperation can then extend national agencies' investigatory power and are an important addition to their regulatory capacity (Efrat & Newman 2018). As such agreements increase the effectiveness of cross-border supervision, it is crucial to understand the barriers and constraints to their formation (see IMF 2007). Then, one can think more clearly about institutional solutions that facilitate cross-border collaboration and promote information sharing and enforcement cooperation between regulators (see Brummer 2011).

To empirically test the hypothesized network effects, a longitudinal network analysis of the evolution of interagency agreement formation over time is presented. The data on which the analysis is based are an original, self-coded data set in which bilateral information exchange agreements (in the form of Memoranda of Understanding, or MOUs) between national securities' agencies (n = 143) are mapped out over a 18-year period. This transnational network of securities agencies has developed as an increasingly dense network of MOUs and serves as a plausibility probe for studying network effects in regulatory networks. In particular, this article applies Stochastic Actor-Oriented Models for non-directed networks to test our hypotheses (see Snijders *et al.* 2010).

Methodologically, the use of Stochastic Actor-Oriented Models is a considerable step forward from conventional uses of network analysis in the literature (e.g. Bach & Newman 2010; Maggetti & Gilardi 2011), as it allows us to better take into account the network dynamics of the way in which transnational patterns of collaboration evolve over time. These network dynamics are important to consider because each tie change modifies the state of the network and later changes build on/are reliant on this new state (Snijders & Pickup 2017). Networks are thus characterized by relational interdependence. However, scholars analyzing transnational networks typically use cross-sectional data and regression-based approaches. While the former are problematic in terms of causality (particularly their inability to establish temporal order and separate selection and influence effects), the latter assume independence of observations, thus failing to account for the interdependence inherent to networked collaboration (Maoz 2012).

In the following, this article firstly discusses and justifies the research context of this study. This gives a better understanding of the substantive questions behind the analysis and the applicability of a network analytical perspective to transnational forms of collaboration between regulatory agencies. Then, a theoretical argument is presented on the kinds of network effects we expect in the context of regulatory cooperation. After discussing the operationalization of the core variables, the basics of stochastic actor-oriented modeling are explained, as well as its (analytical) leverage in understanding processes of network evolution. The analysis tests the hypotheses, after which a conclusion reports the main implications of this study and sets out directions for future research.

2. Research context: Transnational collaboration between securities regulators

Although many regulatory sectors have seen the emergence of cross-national forms of collaboration between regulatory agencies (see Eilstrup-Sangiovanni 2009; Newman & Zaring 2013), international finance has been at the forefront of these developments. Within this sector, an "alphabet soup" of regulatory networks has developed (Ahdieh 2015), including the Basel Committee on Banking Supervision, the Financial Action Task Force (FATF), the International Association of Insurance Supervisors (IAIS), and the International Organization of Securities Commissions (IOSCO). Moreover, besides these more institutionalized forms of multilateral cooperation (see Lall 2015), regulatory agencies also cooperate bilaterally on a more ad hoc basis.

These developments are primarily driven by increasing internationalization of capital markets, calling up the need for cross-national collaboration between national regulatory authorities, as to maintain effective market oversight. Emerging economies, such as those of Brazil, China, Turkey, and India, become increasingly integrated into the global economy not only through trade but also through capital flows into their equity and debt markets. Moreover, stock exchanges have become virtual facilities that can be accessed via trading screens located in any number of broker-dealers' offices. As a result, money can flow anywhere, instantly, regardless of national origin and boundaries. Taken together, these developments have created new and previously unimagined risks, seriously undermining the authority and control of (national) regulators (see Brummer 2011).

Within the field of securities, a particular problem that emerges from the observation that trading networks and market activity increasingly cross multiple jurisdictions is that national regulators have more difficulty accessing information that would expose fraudulent or highly risky trading activities (Simmons 2001, p. 612). This requires national regulators to exchange information with foreign counterparts and engage in various forms of bilateral and multilateral enforcement cooperation. As a result, an increasingly dense web of bilateral agreements has emerged among financial sector regulators. These agreements typically take the form of "Memoranda of Understanding" (MOU), which coordinate cross-jurisdictional relationships between agencies.

Although each MOU typically has its own particularities, most involve the enhancement of the signatories' enforcement powers and the identification of cross-border points of contact for enforcement purposes (Brummer 2009, p. 337). In particular, these agreements establish a procedure by which information is gathered and specify what kind of information will be provided by the foreign agency. A typical MOU calls on each regulator to pass on information that may indicate a breach of the laws of the other party. Some MOUs also grant mutual authority for on-site inspections of fund managers in each other's jurisdictions (Simmons 2001, p. 613). All in all, MOUs enhance cooperation, promote information sharing and knowledge exchange between regulatory agencies, and cultivate trust between partner agencies (Brummer 2009, p. 338). Still, in choosing partners with whom to engage in bilateral MOUs, several uncertainties can be noted.

First, given that MOUs facilitate the exchange of sensitive and potentially damaging information, unreliable partners are not suitable for cooperation. Agencies may have concerns regarding leaks or misuse of information that potentially damages security, commercial, or other interests. Moreover, if confidential information leaks into the public domain, this may harm individuals involved in regulatory investigations and threaten the reputation of the information providing authority. Also, the recipient might misuse information by using it for some other purpose than intended (Yang & Maxwell 2011). Risks for defection and uncertainty about the reliability of partners are thus present in the formation of bilateral agreements, and the information-providing agency needs assurances that exchanged information is handled in an appropriate manner (i.e. "due process").

Second, not all potential partners have the necessary capabilities (or willingness) to fulfil the conditions of an MOU, particularly regarding national enforcement competences and available staff and resources. For agencies requesting information, there is thus a risk that information is only shared selectively or not in a timely fashion. These considerations potentially disrupt the reciprocal nature of cooperation, particularly when only one of the agencies lives up to the conditions set by the agreement (see Singer 2004). Agencies thus require information on whether potential partners have the physical/resource ability to obtain requested information (locating and interviewing suspects) as well as the legal ability to transfer information (e.g. bank-secrecy laws) (see Efrat & Newman 2018). Later, the theoretical framework further discusses the implications of these considerations and translates them into expectations regarding partner selection in bilateral agreement formation.

3. Theoretical framework

A long-standing scholarship on interorganizational collaboration argues that organizations typically form ties with each other in response to interdependencies that shape their common environment (Galaskiewicz 1985; Provan *et al.* 2007; Isett *et al.* 2011). From this perspective, network relationships emerge out of functional necessity and help to solve specific problems. As noted in the introduction of this article, the formation of bilateral agreements between regulators can also be understood from this perspective (see Lazer 2001), that is, as a result of the internationalization of markets and the need to regulate cross-border market activity. The pattern of relationships within a network can thus be explained from agencies' inducements or incentives to collaborate (see O'Toole 1997; Ahuja 2000).

However, such perspectives typically underestimate the difficulties that agencies face in determining with whom to form such network ties (Gulati & Gargiulo 1999; Lee *et al.* 2012). In particular, we note the challenges associated with obtaining information about the competencies, needs, and reliability of potential partners (see Feiock & Scholz 2010). Considering that the formation of bilateral agreements typically results in some form of enduring commitment between partners and carries possible risks for defection, uncertainty about with whom to engage in such agreements is relevant for regulatory agencies as well (see Dawes *et al.* 2009). Imperfect information about partners raises search costs and risks of exposure to opportunistic behavior (Feiock *et al.* 2009).

To help reduce these search costs and alleviate the according risks of opportunism, scholars have underlined the important role that the existing structure of relationships within a network can play (see Gulati & Gargiulo 1999; Feiock & Scholz 2010). To deal with decision-making uncertainty, the network by which agencies are embedded can serve as a repository of information on the availability, competencies, and reliability of prospective partners (see Powell *et al.* 2005). In particular, the positions that actors occupy within a network signal their willingness, experience, and ability to enter partnerships to others. By taking these information signals into account, agencies can reduce uncertainty in their decisionmaking regarding the selection of appropriate partners for collaboration.

Each time an agency chooses a partner by forming a bilateral agreement, this decision thus has informational value for other actors in the network, subsequently affecting future agreement formation. What follows is that network evolution (and partner selection) is an iterative process, in which newly created partnerships modify the previous network, subsequently shaping the formation of future ties. As the network develops over time, it internalizes more information about potential partners, guiding agencies' choices about future alliances (Gulati &

Gargiulo 1999; Henry *et al.* 2010). The following section hypothesizes on the kinds of patterns that can then be expected in the formation of bilateral agreements between agencies.

3.1. Three hypotheses on network effects

First, the notion of triadic closure is important to understand when talking about network dynamics. This idea states that the presence or absence of network ties between two actors is crucially determined by contacts with (shared) third-party actors. These third-party actors can serve as indirect channels for information and reputation effects, for example, by signaling or providing information about the trustworthiness of potential partners (Carpenter *et al.* 2004; Lee *et al.* 2012). Indirect ties thus help organizations mitigate the risks of choosing unreliable partners (Gulati & Gargiulo 1999; Feiock *et al.* 2009), as endorsements and referrals from common partners provide information regarding a potential partner's quality and motives (Burt & Knez 1995). In terms of empirical patterns, one then expects that if both a network tie between actors A and B, and between actors A and C exist (at point t), there is a higher likelihood, ceteris paribus, that a tie between actors B and C will come into existence (at point $t + 1$). Tie formation thus primarily works through referrals, leading to the hypothesis (H1) that:

H1. *Agencies are more likely to form bilateral agreements with agencies to whom they are already indirectly linked.*

Second, a common tendency for network actors is to attach to popular alters. This tendency, known as preferential attachment (Barabasi & Albert 1999), is borne out of several mechanisms. First, if organizations are uncertain about with whom to form network relationships, the popularity of actors may signal that they are preferable partners (Feiock *et al.* 2012). Highly connected agencies convey trustworthiness and reliability more credibly than unconnected agencies (Kinne 2013). Secondly, reputational considerations may also play an important role in this regard, in which attaching to popular alters potentially increases the legitimacy of the core agency as well (Baum & Oliver 1991). Overall, these mechanisms create a "Matthew effect" in which agencies that already have a high number of agreements will accumulate more over time (see Merton 1968). This leads to the hypothesis (H2) that:

H2. *Agencies are more likely to form bilateral agreements with agencies that already maintain a large number of ties.*

Third, the concept of structural (or status-based) homophily describes the idea that actors with similar status are more likely to form relationships (Chung *et al.* 2000; Ahuja *et al.* 2009). The underlying mechanism here is the assumption that high-status individuals expect low-status actors to be unable to reciprocate their efforts in future collaborations (Gould 2002). Forming a network tie with another high-status actor thus seems a plausible strategy to avoid risks of defective behavior or unproductive network relationships. Moreover, if the quality of agencies is hard to assess, signaling effects become an important replacement on which to base partner selection choices (see Podolny 1994). Low-connected actors provide few signals and will thus not be easily seen as a reliable partner. As an extension to the second hypothesis, the third hypothesis (H3) thus states that:

H3. *Agencies with a high number of ties are more likely to form agreement with other agencies that have a high number of ties.*

3.2. Accounting for alternative explanations

Besides (endogenous) network effects as specified in our hypotheses, other tendencies may also account for the evolution of the network of securities regulators. Controlling for these alternative explanations of tie formation patterns allows one to better isolate the hypothesized relationships and assess whether network effects still make a difference for the way in which the network of bilateral agreements between securities regulators evolve over time. Five main categories of control variables are specified.

Firstly, agencies that are closer together may also be more likely to collaborate. The geographic proximity of agencies is thus something to take into account (see Cao 2012). Secondly, homophily based on actor characteristics has also been important to understanding the formation of interorganizational network relationships (Kraatz 1998; Efrat & Newman 2018). Regulatory agencies might expose a preference for collaborating with agencies they perceive as "similar" with regard to certain characteristics, for example, in terms of market size or administrative tradition. Thirdly, agencies that are more interdependent due to the existence of high volume capital or trade flows between them are also more likely to collaborate, regardless of pre-existing network ties. Fourthly, countries that are already engaged in other forms of collaboration, for instance through trade agreements or regulatory cooperation in other sectors, may find it easier to also cooperate in the regulatory field of securities. Lastly, besides bilateral collaboration, agencies also engage in multilateral platforms. Frequent interaction within such multilateral platforms increases the chance of also engaging in a bilateral collaboration, as it potentially establishes agencies as a trustworthy partner.

4. Data and methods

To reconstruct the network of bilateral relationships between securities regulators, longitudinal data were collected on the formation of bilateral Memoranda of Understanding (MoU), from the 1980s onwards. To determine the membership of the network, agencies listed as members of IOSCO (the largest institutional platform for transnational collaboration between securities regulators) were used as a basis. For non-member jurisdictions, it was checked whether they had a separate securities agency or commission and, if this were the case, these were added as well. This provided a comprehensive list of 143 securities regulators. However, given the longitudinal nature of the analysis and the consideration that many agencies in our network did not exist for larger parts of the 1980s and 1990s, network membership varies over time. To account for the changing composition of our network, agencies were added to the network in the year in which it came into existence based on the creation year of agencies stated in their respective establishment acts.

Given that no data set of bilateral agreements was available, the relationships between securities agencies were self-coded. To do so, the "international cooperation" sections typically maintained on the securities' regulators websites were first consulted. Second, this information was cross-checked with evidence from annual reports and press releases, allowing for the identification of the dates of initiation of bilateral agreements. Third, for the agreements that were only one-sidedly reported, the signed documents were checked to validate the relationship. To be conservative, the data set excluded relationships that were only reported one-sidedly, lacked a year of signing, and for which the official document or other documentation could not be retrieved. Note that only coded agreements specifically related to securities were included, and not those in the domains of banking or insurance (which is sometimes done by the same agency).

The collected bilateral agreements were coded into adjacency matrices for each year of analysis.[1] The existence of a relationship was coded as a "1" when present and "0" otherwise. Note that data were only collected on the creation of ties, resulting in a longitudinal data set in which ties are added over time, but never terminated. For agencies that were not yet in existence in particular year, their relationships were coded as "structural zeroes," indicating that the existence of ties for these agencies was impossible (see Ripley *et al.* 2018, p. 31). The membership of the analyzed network thus varies over time, taking into account the year in which agencies were created and could start to form network relationships. All in all, this resulted in a panel data set on the existence of network relationships between 143 regulatory agencies, for a period of 18 years (1999–2017).[2]

4.1. Control variables

For the control variables on agency characteristics, data were gathered on the market capitalization of countries throughout the years, as well as more general financial economic information. In particular, the World Bank's classification of economies based on GNI was used, allowing for division of jurisdictions into four categories (from low- to high-income countries). For market capitalization, data from the World Federation of Exchange Database were taken. Given the highly fluctuating nature of this data, the precise market capitalization values were recoded into categories. These categories seem to better reflect the way in which they can be taking into account for regulatory agencies' decisionmaking. More specifically, the small countries for which no market capitalization was reported were coded as a "zero." The other countries were coded onto an ordinal scale in which the group of smaller markets (between 0 and 100.000.000) were given a "1," and every 10-fold increase in market capitalization represents a category increase (with the largest market being assigned a "6").

To measure *regulatory independence*, the legislative acts by which regulators were declared independent were traced backed, and this year was subtracted from 2017 (Jordana *et al.* 2011). This gives a quantitative indicator that serves as a proxy for the independence of an agency. To capture the political-institutional context of countries, the data set of Bianculli *et al.* (2013) on the different *administrative traditions* of countries was used. For countries that were not reported in this data set, the QOG data set and the Painter and Peters (2010) book were used for further categorization. Activity within IOSCO was based on working group and commission membership data of agencies within IOSCO, available through their website. This information was coded into the number of working groups in which agencies participate. The year in which agencies adopt IOSCO's Multilateral MoU (MMoU) was also taken into account. This is a multilateral standard on information exchange and enforcement cooperation and potentially interferes with tie formation behavior regarding bilateral MOUs (see Austin 2012).

To capture the *geographical proximity* of pairs of actors, agencies were subdivided based on the country regions identified in the QoG data set (Teorell *et al.* 2018). For data on regional platforms, the existing institutional platforms in the field of securities regulation were identified and an affiliation matrix[3] was constructed based on the corresponding membership information. EU regulators were coded separately, given that they participate in the most institutionalized form of regional cooperation, namely CESR/ESMA (Howell 2017). Lastly, to capture trade/prior agreements between countries, information from the DESTA data set on trade agreements was included by coding all bilateral base-treaties between countries (Dür *et al.* 2014).[4]

5. Analytical strategy

The primary challenge of analyzing network data is dealing with relational interdependence. Regression-based analyses of network effects typically assume that observations are independent, which is inherently problematic for analyzing networked settings. Traditional estimation methods (including standard count and survival models) then potentially lead to biased estimators (see Steglich *et al.* 2010).

To account for these shortcomings, ERGMs have gained prominence as a method of statistical inference for network analysis (Lubell *et al.* 2012; Lusher *et al.* 2013). However, ERGMs are traditionally used for the estimation of effects in cross-sectional data and do not have an explicit actor-level focus (see Block *et al.* 2016). Given the interest of this study in the choices of individual actors over time, a Stochastic Actor-Oriented Model (SAOM) of network evolution is used.[5] This type of statistical network model takes the formation of network relationships as its dependent variable and allows one to model endogenous and exogenous influences that potentially drive this process (Snijders *et al.* 2010). Changes in a network are assumed to result from the purposive decisions of individual actors, who evaluate their positions and adjust their ties as to maximize their utility. Actors are thus assumed to "make the changes" in the networks, which is consistent with this article's theoretical argument of strategic choice in the formation of bilateral network relationships (see also Kinne 2013).

The basic idea of SAOMs is that it defines the totality of possible network configurations for a given set of actors as a state space of a stochastic process, and then models the observed network dynamics by specifying parametric models for the transition probabilities between these states (Snijders *et al.* 2010). When working with panel data, each measurement of the network corresponds to one state in the overall state space and we explain network dynamics by looking at the transition probabilities by which the network "jumps" from one observation to the next. The first observation is conditioned upon and is thus taken as the exogenously given starting value of the stochastic process.

Because the set of possible transitions between states is potentially very large, some simplifying assumptions are needed. Firstly, it is assumed that the transitions between panel measurements are manifestations of an underlying process (i.e. of network evolution) taking place in continuous time. Secondly, actors are assumed to act conditionally independent of each other and only make decisions given the current state of the network (Markov property). Thirdly, actors change at most one tie variable at a time. Observed transitions are then modeled by decomposing them into network "mini-steps." A *rate function* indicates the speed at which the network actors get an opportunity to make such changes, while the *objective* function indicates what such changes actually look like.

The parameters of the network objective function thus represent the direction of changes in network ministeps. These can be understood as behavioral rules that determine changes in network ties. For each actor, the probabilities of the choices to maintain, dissolve, or establish a relationship with another agency are an increasing function of the expected utility as calculated from the variables in the model. Probabilities of these tie-changes are in part endogenously determined, that is, as a function of the current network structure itself, and in part exogenously determined, as a function of characteristics of the nodes ("actor covariates", e.g. regulatory independence) and of characteristics of pairs of nodes ("dyadic covariates", e.g. similar administrative traditions).

Because the estimation of parameters is highly complex and cannot be calculated analytically (e.g. through maximum likelihood procedures), they are approximated by Monte Carlo simulations. What this means is that the researcher selects a vector of statistics, and then determines the parameter estimate as the parameter value for which the expected value of this vector of statistics equals the observed value at each observation (Snijders & Pickup 2017). The basic idea is that the network dynamics are simulated many times with trial parameter values. These values are then updated until the averages of a suitable set of network descriptives, reflecting the estimated parameters, are close enough to the observed values. This process is repeated until the algorithm converges, although sometimes it is necessary to repeat the estimation, taking the earlier obtained parameters as new initial values.

5.1. Modeling the formation of undirected network relationships

In transnational political and organizational settings, non-directed collaborations and agreements between actors are more typical, potentially changing the dynamics by which networks evolve (see Snijders & Pickup 2017). In such non-directed ties, actors on both sides have a say in its existence, requiring specific assumptions about the negotiation and coordination between actors in terms of tie creation and termination. Ties thus have no directionality, in the sense that $X_{ij} = X_{ji}$ and they are treated as one and the same variable. For undirected networks, the same effects can be used as for directed networks, although some are now redundant (because i - > j and j - > i are now equivalent).

Snijders and Pickup (2017) propose five undirected network models to capture this dynamic of non-directed networks. For the kind of network relationships studied in this article, "unilateral initiative and reciprocal confirmation" are chosen. In this model, it is assumed that one actor takes the initiative and proposes a new tie; if the actor proposes a new tie, the other has to confirm, otherwise the tie is not created (Ripley *et al.* 2018, p. 50; see Snijders & Pickup 2017). This process best captures the way in which bilateral agreements between national agencies are formed in practice.

6. Analysis

To test the hypotheses, network influences are modeled into the objective function of our SAOM.[6] For the triadic closure effect, a (undirected) transitive triads effect is included, which captures the prediction that agencies prefer agreements that lead to closed triads. More specifically, the GWESP effect[7] was chosen, which places decreasing weights on higher numbers of shared partners (Snijders *et al.* 2006). For the preferential attachment hypothesis a popularity effect was included, which captures the tendency of agencies with a high degree (i.e. a large number of bilateral MOUs) to attract additional ties *because* of their current high-degree value. To capture the network effect of the third hypothesis, a general assortativity effect was included, which captures the tendency of high-degree nodes to be connected to other high-degree nodes (see Newman 2002). Lastly, for the most important type of control variable, that is, homophily effects with regard to actor characteristics, similarity effects on various dyadic covariates were included. These effects indicate whether agencies that share a value on certain characteristics (such as administrative tradition, or shared market size) are more likely to form agreements.

Note that the overall analysis was divided into two time-periods: 1999–2008 and 2008–2017.[8] This is partly a modeling choice, as shorter periods reduce time-heterogeneity, in which parameter values shift too heavily over time, creating convergence problems (Lospinoso *et al.* 2011). In addition to this technical consideration, subdividing the analysis in smaller time periods also helps to account for important exogenous events that are relevant to the studied research context. The year 2008 was taken as a cut-off point and resulted in two 10-year periods of analysis, giving a substantively interesting pre- and post-financial crisis subdivide. Given the large role securities played in the global financial crisis (see Shiller 2011), this seems like an important exogenous event to consider.

6.1. Visualizations and descriptive statistics

Figure 1 provides a visual representation of the network over time. The nodes represent regulatory agencies and the ties between them signify the existence of a bilateral MOU. The size of the nodes represents the number of bilateral MOUs an agency maintains (also referred to as the *degree* of an agency). Visualizations for four years

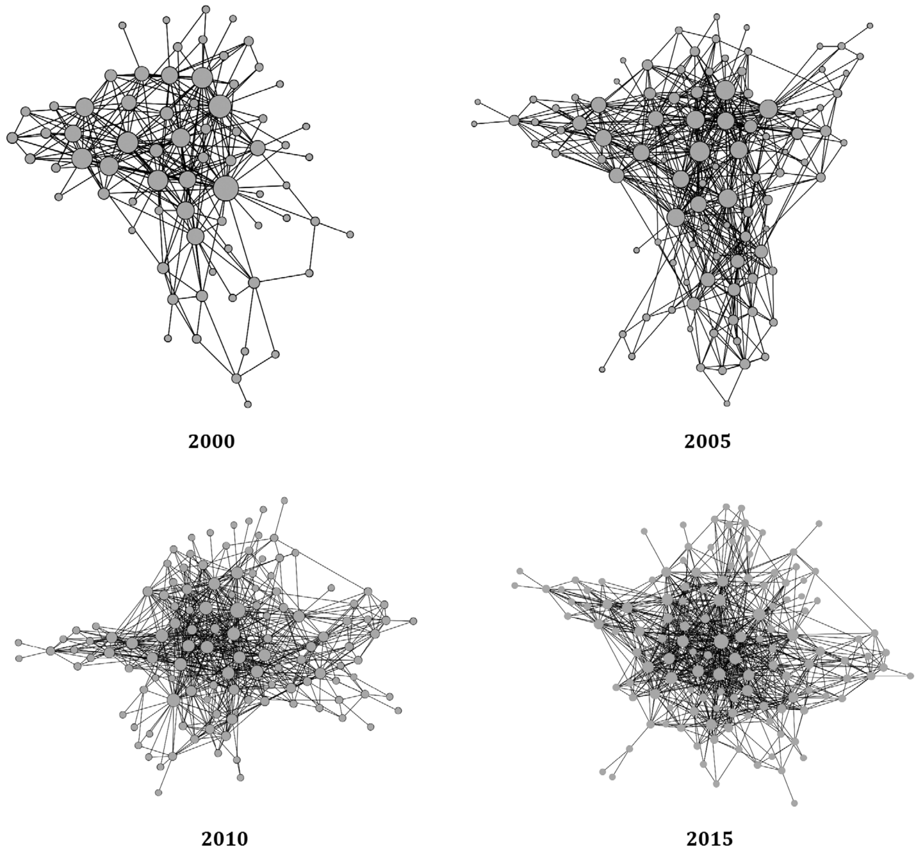

Figure 1 Network visualizations (2000, 2005, 2010, 2015).
Legend: Node size represents degree centrality.

are shown (2000, 2005, 2010, and 2015). Over time, more agencies become active in the network and start to form bilateral MOUs. Also, the number of high-degree nodes clearly increases, as more large-size nodes emerge in the center of the network visualizations.

Figure 2 provides histograms for the degree distributions in our data. The x-axis represents the degree, while the y-axis represents how many nodes have a certain degree (i.e. the number of ties they maintain). Over time, more agencies accumulate a larger number of network ties, although a high number of low-degree nodes remains throughout. The skewed distribution characterizing our network data seems to be the first indication of the presence of preferential attachment mechanism (see Newman 2005). In Table 1, the descriptives of our network data are given.

7. Results

The results of the explanatory analyses are presented in Table 2. Despite the division into two analysis periods, both initial models presented in Table 2 had significant time heterogeneity, primarily due to the inclusion of several control variables. Time heterogeneity means that parameter values shift too heavily over time for the model to give a reliable estimation and this potentially leads to bias in parameters of interest (see Lospinoso *et al.* 2011). A first option to deal with time heterogeneity is to include dummy variables for time heterogeneous effects. However, given the large number of effects and time waves for which dummies would have to be included, the model would become overly complicated.

As a solution for both models, the effects for which the most severe time heterogeneity was detected were removed from the model (denoted by "NA"). This solved the issue of time heterogeneity for the overall model, providing a more reliable estimation of the parameters of our core effects. In Table 2, the results of the different models are shown next to each other (periods "a" and "b"), while the second models are interpreted in-text later.

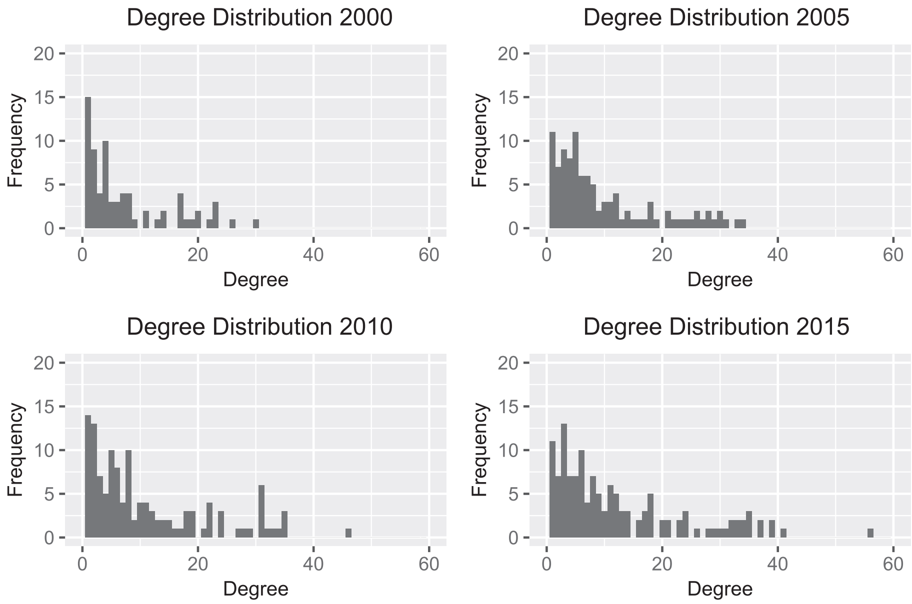

Figure 2 Degree distributions network data (2000, 2005, 2010, 2015).

Note that for both models, goodness-of-fit tests show adequate results in the sense that the values produced by the simulation models are close enough to the values in the data. A visualization of these tests is given in Appendix A. Also note that the full models, including rate parameters, are given in Appendix B (Table A1).

The parameters in Table 2 capture the changes that agencies make in their network, in terms of the formation of ties. The direction of the parameter values indicates whether agencies make choices that increase or decrease the statistic associated with the parameter (e.g. more or less triads). Parameter sizes can be translated to (conditional) odds ratios. They thus represent the respective probability that agency i will choose one particular tie to j over another, given that the only difference is a one-unit change in the covariate of interest (see Kinne 2013; Ripley *et al.* 2018). However, given that a precise interpretation of these numbers are problematic (and potentially unrealistic), significant estimators are held to indicate that agencies, in their partner selection choices, have an overall tendency for the effect captured by the included statistic in the model (e.g. a tendency toward triadic closure).

7.1. Analysis period 1999–2008

Regarding the hypotheses of interest, the first period of observation (1999–2008) shows that the *triadic closure* parameter has a significant positive value (b = 1.566; *S.E.* = 0.302), meaning that there is a tendency for agencies to close open triads. In other words, friends of friends tend to become friends over time, providing evidence that tie formation in the MOU network works through referrals/third-party actors. Note that rather than a standard triadic closure effect, we included the GWESP effect, which places decreasing weights on a higher number of shared partners. In other words, the first two shared partners are more likely to lead to triadic closure than the

Table 1 Network descriptives 1990–2017

Observation time	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
Number of actors	46	52	59	67	72	80	88	92	101	106	110	118	121	122
Number of ties	14	24	41	65	84	103	132	167	214	242	271	314	360	403
Average degree	0.61	0.92	1.39	1.94	2.33	2.58	3.00	3.63	4.24	4.57	4.93	5.32	5.95	6.61
Observation time	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Number of actors	127	131	135	135	135	136	140	141	141	143	143	143	143	143
Number of ties	448	503	543	582	616	649	677	701	730	755	784	811	831	851
Average degree	7.06	7.68	8.04	8.62	9.13	9.54	9.67	9.94	10.35	10.56	10.97	11.34	11.62	11.90

sixth or seventh (see Snijders *et al.* 2006). Both the *popularity effect* (H2) and the *assortativity effect* (H3) do not seem to make a difference for tie formation patterns.

In terms of the control variables, some interesting patterns also emerge. Most prominently, both shared administrative traditions (b = 0.634; *S.E.* = 0.131) and income classifications (b = 0.626; *S.E.* = 0.121) are strong predictors for the tendency of agencies to form ties among themselves, pointing to *homophily* effects regarding actor characteristics. Also, for MOU formation between agencies, it seems to matter whether the countries they represent already have a trade agreement in place (b = 0.821; *S.E.* = 0.178). Regarding the other variables in our model, note that the more active agencies are within IOSCO working groups, the higher the likelihood that they will form ties in general (b = 1.634; *S.E.* = 0.355), and whenever both agencies have signed IOSCO's MMoU they have a lower tendency also form a bilateral MOU (b = −0.388; *S.E.* = 0.177). For some agencies, multilateral agreements thus partly replace the function of bilateral agreements.

Lastly, for the three parameters for which significant time heterogeneity was detected, note that in the first model, years of independence seemingly decreases the likelihood of agencies to form ties in general (b = −0.216; *S.E.* = 0.047). This is seemingly explained by the consideration that agencies that have existed for a longer time, already had many MOUs in place before the period of analysis started. Also note that the geographical proximity and regional platform parameters were excluded, although these effects were not significant drivers of tie formation to begin with.

7.2. Analysis period 2008–2017

For the second period of analysis, many of the core effects remain, although some have changed in strength. Regarding the first hypothesis, this period still shows a strong tendency toward *triadic closure* (b = 1.791; *S.E.* = 0.376). However, the other main effects regarding the hypotheses on *preferential attachment* and *degree assortativity* still make little difference to understanding patterns of tie formation.

Regarding *homophily* effects based on actor characteristics, note that regulatory agencies that have a similar administrative tradition still have a higher likelihood of also forming a bilateral MOU (b = 0.761; *S.E.* = 0.201). However, similarity regarding income classifications no longer makes a difference (b = 0.149; *S.E.* = 0.166). For the other included effects, *geographical proximity* now has a positive and significant parameter value in this period of analysis (b = 0.853; *S.E.* = 0.220). Agencies from countries that are closer together are more likely to connect, indicating that patterns of tie formation are structured according to geographical regions.

The three parameters for which significant time heterogeneity was detected in this model were *Regulatory Independence*, *MMoU adoption alter*, and *MMoU adoption similarity*. All three of these effects had a significant

Table 2 Results SAOM–analysis bilateral MOUs over time

	Period 1a (1999–2008)		Period 1b (1999–2008)		Period 2a (2008–2017)		Period 2b (2008–2017)	
Variables	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
Network dynamics								
Triadic closure (h1)	2.004*	(0.407)	1.566*	(0.302)	1.910*	(0.415)	1.791*	(0.376)
Popularity effect (h2)	0.010	(0.051)	0.077	(0.040)	−0.001	(0.049)	0.047	(0.032)
Assortativity effect (h3)	0.060	(0.104)	−0.068	(0.079)	0.207	(0.129)	0.061	(0.079)
Indirect ties	−0.023	(0.043)	−0.077	(0.036)	−0.039	(0.036)	−0.055	(0.032)
Geographic. proximity	−0.187	(0.185)	NA	NA	0.923*	(0.236)	0.853*	(0.220)
Shared Adm. tradition	0.643*	(0.157)	0.634*	(0.131)	0.628*	(0.210)	0.761*	(0.201)
Regulatory Indep.	−0.216*	(0.047)	NA	NA	−0.547*	(0.170)	NA	NA
Regional platforms	0.225	(0.161)	NA	NA	−0.322	(0.229)	−0.521*	(0.215)
IOSCO activity	1.701*	(0.408)	1.634*	(0.355)	−0.056	(0.843)	−1.304*	(0.238)
Shared market Cap.	−0.095	(0.138)	−0.056	(0.136)	0.060	(0.172)	0.100	(0.169)
Shared income	0.704*	(0.123)	0.626*	(0.121)	0.228	(0.165)	0.149	(0.166)
Trade treaty	0.791*	(0.181)	0.821*	(0.178)	0.119	(0.294)	0.167	(0.292)
MMoU adoption alter	−0.494*	(0.223)	−0.628*	(0.224)	−0.229	(0.261)	NA	NA
MMoU adoption similarity	−0.388*	(0.183)	−0.383*	(0.177)	−0.566*	(0.195)	NA	NA

All convergence t-ratio's < 0.06. Overall maximum convergence ratio 0.12. *Significant at the .05 level.

negative parameters value, meaning that they lowered the tendency for agencies to create ties. Excluding these effects potentially explains the inflation of *IOSCO activity*, which now has a large negative parameter value (b = −1.304; *S.E.* = 0.238). For these effects, time heterogeneity seems to be an intrinsically interesting phenomenon in itself. However, given that the exclusion of these effects did not significantly alter our main parameters of interest, a further in-depth analysis of time heterogeneity effects currently exceeds the scope of this article.

7.3. Interpretation of findings

Overall, the analysis showed a strong triadic closure effect for both periods. In particular, the GWESP effect provided a good fit, meaning that in its effect on the likelihood of tie formation, the number of shared partners between agencies has decreasing returns. In other words, the first shared partner has a stronger effect on the likelihood for tie formation than do the 6th of 7th shared partner. Although triadic closure is sometimes interpreted as to be driven by an externalities mechanism, in which shared partner create a stronger interdependence between actors raising the likelihood for tie formation among them (see Kinne 2013), this observation of decreasing returns raises confidence in an information mechanism being at work. After all, for the externalities mechanism, we would expect the likelihood of tie creation to increase with each additional shared partners, a pattern not found in the data.

Note that the absence of an assortativity and popularity effect also allow us to draw some conclusions about the way in which information signals play a role in the formation of inter-agency network ties. The number of ties an agency maintains (i.e. its degree centrality) apparently tells us relatively little about the way in which future ties develop. This means that either degree centrality is not a very good operationalization for measuring high status or popular agencies, and that proxies such as market size are potentially a better candidate. Or it could mean that status or reputation is simply not an important consideration for agencies when forming bilateral agreements.[9] This latter point may reflect the consideration that, given the extensive time and effort that can go into negotiating such agreements (see IMF 2007, p. 109), there should always be an instrumental purpose underlying their formation. A triadic closure effect is compatible with such an instrumental purpose, given that it assumes the initiation for such agreements to have a functional necessity, but that the potential uncertainties underlying such agreements leads to the expectation that such agreements are more likely to form when agencies have shared partners than when two agencies are otherwise unconnected. With the other two types of explanations, however, this complementary function is apparently lost, given that popularity effects purely rely on status or reputational considerations, and the assortativity effect means that limiting the formation of agreements with similarly connected agencies undercuts its instrumental purpose of cross-border collaborations.

Regarding exogenous factors driving network formation patterns, we should consider the high value of institutional activity within IOSCO. This may reflect the consideration that "institutionally active" agencies get their information signals about other regulators from institutionalized multilateral platforms. In other words, agencies active within the institutionalized settings of IOSCO more often meet other regulators in the working groups or committees part of these settings, and can estimate the reliability of a partner through participating in these settings. Triadic closure mechanisms might then primarily be important for those not very active in these kinds of settings, which is, based on the working group participation within IOSCO, still the biggest part of agencies in the sample (99 out of 143). Still, we should also note that those active within multilateral setting may simply have a higher need for transnational collaboration and that this explains their higher likelihood to form agreements.

Lastly, the significance of several homophily effects regarding agency characteristics also points to interesting dynamics regarding inter-agency agreement formation. The significance of such effects may reflect the consideration that for similar countries, the transaction costs of agreement formation are lower. For MOUs in particular, having similar provisions regarding the disclosure of information or presumptions of privacy makes the formation of agreements arguably easier. In that sense, having a similar legal framework or administrative tradition can remove important barriers toward collaboration. Such similarities likely create greater understanding and predictability of each other's behavior (see Baccini 2014; Efrat & Newman 2018).

8. Discussion and conclusion

This article assessed the applicability of a network analytical perspective to study patterns of tie formation in a transnational network of information exchange agreements between securities regulators. This analysis provides clear evidence for the presence of network effects in the formation of bilateral agreements over time. Most prominently, tie formation is driven by *triadic closure*: having shared partners influences the likelihood that two agencies will also form a bilateral agreement among themselves. This finding is consistent with the first hypothesis and supports the line of reasoning that agencies use their existing network relationships as information signals to guide future partner selection choices. Moreover, the effect was robust for different periods of analysis and the inclusion of a number of potential alternative explanations.

However, other hypothesized network effects hardly play a role in tie formation patterns over time. Mechanisms of *preferential attachment* and *degree assortativity* provided little explanatory leverage in the context of information exchange agreements between regulatory agencies. This questions the applicability of these theoretical insights – primarily derived from studies of interfirm partnerships within market settings – to the more public context of regulatory collaboration (see Isett & Provan 2005). Still, *homophily* effects regarding actor attributes *do* play an important role in the formation of bilateral ties, as agencies that share administrative traditions and have a similar sized economy are more likely to form an MOU than agencies that do not share these characteristics. This seems consistent with recent findings from studies that have looked at the importance of (domestic) institutional similarity in the formation of information-sharing agreements (see Efrat & Newman 2018).

All in all, the findings of this article speak to scholars that have looked at globalizing administrative patterns in several ways. First, the study provides a basis for theorizing on the kind of network effects to expect when analyzing how transnational relationships between regulatory and administrative agencies from various jurisdictions form and develop. Although a metaphorical usage of the network concept has long been used to think about such transnational forms of collaboration (see Raustiala 2002; Eberlein & Newman 2008; Bach & Newman 2010), the explicit modeling approach of this study gives these intuitions regarding network effects a more precise theoretical formulation. Second, by utilizing new developments in the field of statistical network models, the analysis demonstrated how these hypothesized effects can be subjected to rigorous empirical testing. In that sense, a type of inquiry that has been applied in the fields of international relations and policy research (see Kinne 2013; Snijders & Pickup 2017) also provides promising directions for the study of transnational regulatory networks.

The policy implications of the presented study should also be considered. In particular, the analysis demonstrated that collaboration is driven by triadic closure and that shared partners can thus help agencies to overcome barriers to collaboration. These findings can be of interest to international organizations and institutions (or domestic agencies) concerned with promoting transnational collaboration and point to the important role they can play in helping agencies overcome these barriers by acting as brokers themselves or by providing platforms or opportunities for agencies to meet. In this way, they can help overcome potential fragmentation emerging from triadic closure tendencies and facilitate collective action at the transnational level (see also Feiock & Scholz 2010). The consideration that IOSCO has partly taken up this role, may explain the insurgence of memorandum-like agreements in the field of securities (see Brummer 2009; Verdier 2009), and serves as a potential guideline for policymakers in other fields as well.

In future research, scholars are encouraged to assess the generalizability of findings beyond the context of transnational collaboration between securities regulators. Given that the form of collaboration studied in this article is typical for many different types collaborative settings (see Yang & Maxwell 2011; Efrat & Newman 2018), we can reasonably expect the network dynamics found in this article to be present in various forms of collaboration relevant to public administration research. However, comparing different research contexts gives us a better idea of how network effects vary across research settings and what particular contingencies potentially influence inter-agency agreement-formation. Moreover, considering the strength of relationships between agencies (e.g. by looking at the extensiveness or number of agreements) or the way in which patterns of collaboration spillover across regulatory sectors may provide promising lines of future inquiry.

Also, scholars should look more carefully into the time dimension of network evolution. Although this study incorporated a longitudinal design that helped us establish temporal order and enabled us to better distinguish between selection and influence effects (Steglich *et al.* 2010), it did not explicitly theorize on how exogenous shocks or factors (financial crises, institutional activity) influence the existence, strength, and directions of network effects over time. However, given the findings of this study, in which the parameter values differed between periods of analysis, this seems a promising avenue for future research. Time heterogeneity is not merely a modeling consideration, but an intrinsically interesting phenomenon in itself (see Lospinoso *et al.* 2011).

Lastly, the specifics of agencies' decisionmaking regarding transnational cooperation warrant further scrutiny. In this article, it is assumed that information or reputational cues play an important role in this regard, emphasizing the way in which agencies use these cues to deal with uncertainty. However, insights about the motivations for actual decisions can only be verified through more in-depth qualitative evidence in which involved actors reveal what they did and why. Then we can also start to think about how these decision-making dynamics might be relevant for other kinds of organizational outcomes, such as decisions of standard adoption (Maggetti & Gilardi 2011) or network membership (Bach & Newman 2014). In that sense, network relationships as an independent variable can potentially be linked to a number of other variables that are of interest to scholars in regulatory decisionmaking. For understanding globalizing administrative patterns as they develop, it will then be important to keep asking who is linked to whom, what is the nature of those linkages, and how do these linkages affect behavior.

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Endnotes

1 Adjacency matrices are $N \times N$ matrices that store network data by signifying whether relationships exist between actors at a given point in time (see Wasserman & Faust 1994).

2 We collected data from 1985 onwards, but due to the highly varying membership of the network in the period until 1999, primarily due to the creation of new agencies, this earlier period was not suitable for analysis.

3 Affiliation matrices record the affiliation of actors to an event, in this case agencies to regional platforms (see Wasserman & Faust 1994, pp. 298–299). Such affiliation matrices allow us to create dyadic covariates that indicate whether or not agencies operate in similar regulatory platforms.

4 Because the European Commission has negotiated all trade agreements on behalf of its members states since 1958, this variables unfortunately does not capture trade agreements with EU countries.

5 Although advanced models such as Dynamic Actor Network Models also exist (Stadtfeld *et al.* 2017), such models require time-stamped data, that is, data in which specific dates are given for the formation of network ties. Given that for the data used in this article, this information was not always available and the analysis uses yearly panels. For such a data structure, stochastic actor-oriented models provide a reliable and developed method of analysis.

6 Because in the network data only the creation of ties is observed, several basic parameters cannot be defined. Most importantly for such "uponly" networks, the outdegree and linear shape effect are not defined because these effects define the balance between the probabilities of going up or going down. This does not apply for networks in which only the formation of ties is observed (see Ripley *et al.* 2018, p. 30).

7 GWESP stands for geometrically weighted edge-wise shared partners.

8 As noted, the first waves of our analysis, from the 1990s onwards, gave too many problems during analysis, particularly regarding convergence and inflated parameter values and standard errors. Therefore, the current analysis focuses on the last 20 years of collected data.

9 As one referee pointed out, a particularly important agency to take into account in this regard is the US SEC, which has been argued to use bilateral MOUs as a means of influence in securities regulation (Bach & Newman 2010; Brummer 2011; Oatley *et al.* 2013). Because of this, additional analysis was done in which an US SEC alter effect was included (i.e. having a tie with the US SEC). Interestingly, this effect had a significant negative parameter value. Substantively, this could be interpreted as an US SEC strategy to push toward the MMoU and forbidding its network partners to still form bilateral ties. However, because the inclusion of this effect did not alter the significance or direction of the effects representing the main hypotheses of this thesis, such explorations exceed the scope of this study and were left out of the final analysis.

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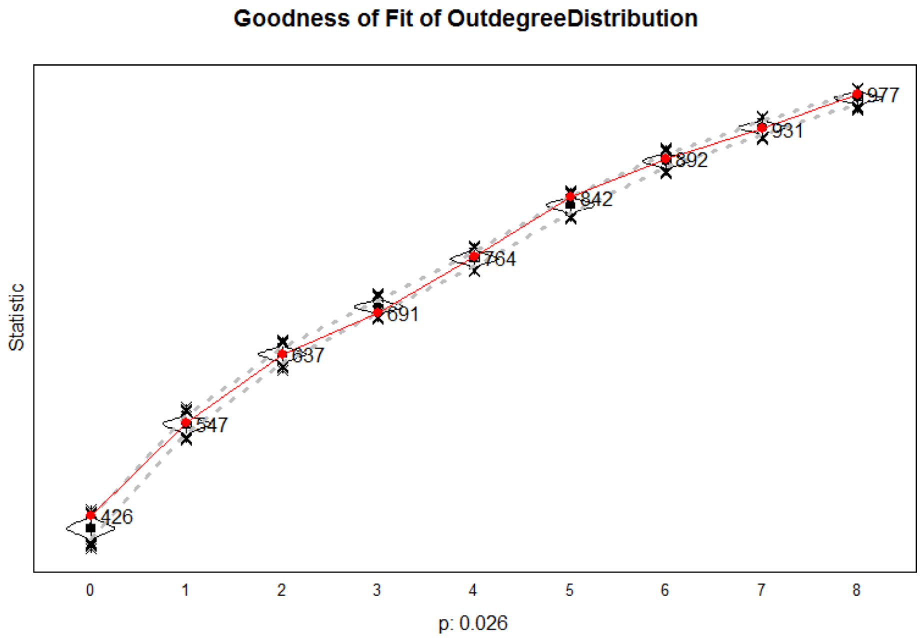
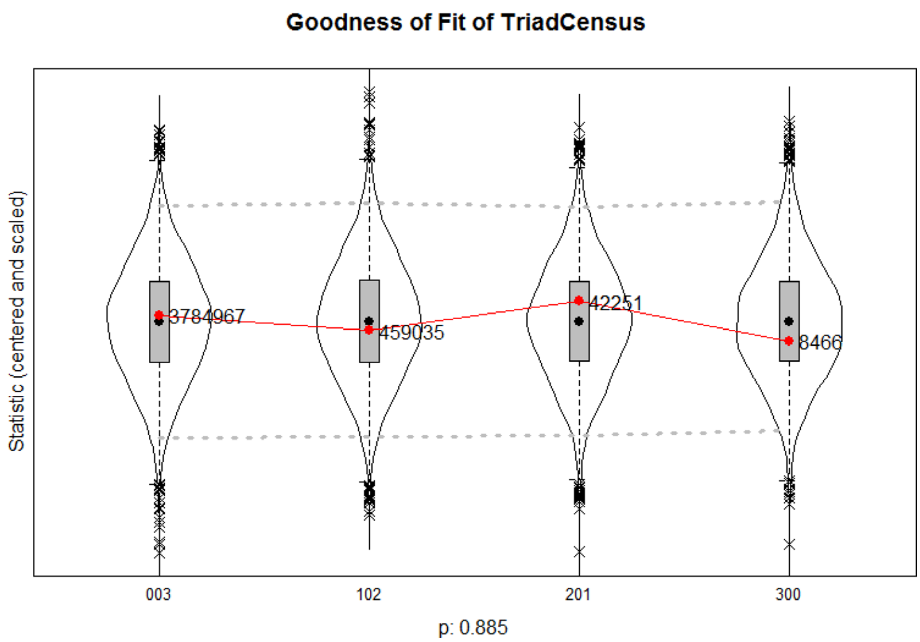
Appendix A – Goodness-of-fit statistics

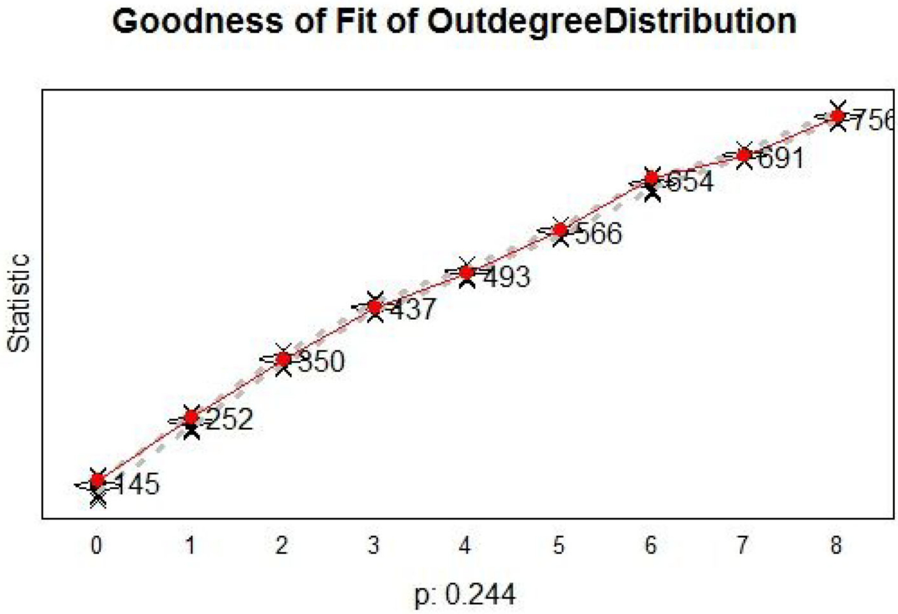
Goodness-of-fit statistics check whether the RSiena model sufficiently reproduces the characteristics of the observed network. Good fit is established by simulating auxiliary statistics and assessing whether the average values of these auxiliary are close enough to the values observed in the data. This fit is visualized below in which the goal is to have the observed values within the confidence bands of the simulated values. The tested auxiliary statistics are in-/outdegree distributions and triad census distribution. Note that higher *P* values indicate a better fit. For more information, see Schweinberger (2012).

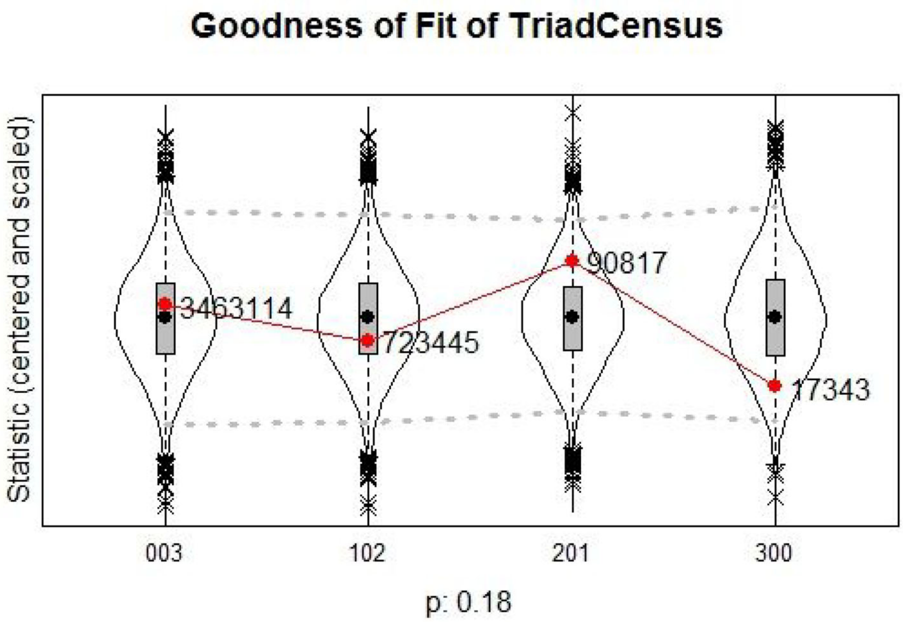
Analysis Period 1999–2008.





Analysis Period 2008–2017





Appendix B – Full models (incl. Rate parameters)

Table A1 Full models SAOM–analysis bilateral MOUs over time

	Period 1a (1999–2008)		Period 1b (1999–2008)		Period 2a (2008–2017)		Period 2b (2008–2017)	
Variables	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
Rate parameters								
Period 1	0.418	(0.078)	0.405	(0.074)	0.343	(0.061)	0.292	(0.051)
Period 2	0.545	(0.088)	0.534	(0.085)	0.274	(0.053)	0.235	(0.045)
Period 3	0.546	(0.081)	0.546	(0.082)	0.234	(0.048)	0.201	(0.041)
Period 4	0.501	(0.078)	0.505	(0.077)	0.279	(0.051)	0.239	(0.045)
Period 5	0.510	(0.076)	0.517	(0.077)	0.238	(0.047)	0.202	(0.040)
Period 6	0.582	(0.078)	0.598	(0.081)	0.268	(0.049)	0.231	(0.043)
Period 7	0.398	(0.062)	0.416	(0.066)	0.247	(0.047)	0.213	(0.041)
Period 8	0.371	(0.059)	0.394	(0.063)	0.182	(0.041)	0.157	(0.035)
Period 9	0.319	(0.055)	0.339	(0.058)	0.180	(0.038)	0.155	(0.035)
Network dynamics								
Triadic closure (h1)	2.004*	(0.407)	1.566*	(0.302)	1.910*	(0.415)	1.791*	(0.376)
Popularity effect (h2)	0.010	(0.051)	0.077	(0.040)	−0.001	(0.049)	0.047	(0.032)
Assortativity effect (h3)	0.060	(0.104)	−0.068	(0.079)	0.207	(0.129)	0.061	(0.079)
Indirect ties	−0.023	(0.043)	−0.077	(0.036)	−0.039	(0.036)	−0.055	(0.032)
Geographic. proximity	−0.187	(0.185)	NA	NA	0.923*	(0.236)	0.853*	(0.220)
Shared Adm. tradition	0.643*	(0.157)	0.634*	(0.131)	0.628*	(0.210)	0.761*	(0.201)
Regulatory Indep.	−0.216*	(0.047)	NA	NA	−0.547*	(0.170)	NA	NA
Regional platforms	0.225	(0.161)	NA	NA	−0.322	(0.229)	−0.521*	(0.215)
IOSCO activity	1.701*	(0.408)	1.634*	(0.355)	−0.056	(0.843)	−1.304*	(0.238)
Shared market Cap.	−0.095	(0.138)	−0.056	(0.136)	0.060	(0.172)	0.100	(0.169)
Shared income	0.704*	(0.123)	0.626*	(0.121)	0.228	(0.165)	0.149	(0.166)
Trade treaty	0.791*	(0.181)	0.821*	(0.178)	0.119	(0.294)	0.167	(0.292)
MMoU adoption alter	−0.494*	(0.223)	−0.628*	(0.224)	−0.229	(0.261)	NA	NA
MMoU adoption similarity	−0.388*	(0.183)	−0.383*	(0.177)	−0.566*	(0.195)	NA	NA

All convergence t-ratio's < 0.06. Overall maximum convergence ratio 0.12. *Significant at the .05 level.