Transnational networks and domestic agencies : making sense of globalizing administrative patterns

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Chapter 2

Network Diffusion and Standard Adoption

ABSTRACT[4]

The soft law measures that transnational regulatory networks produce have become increasingly important in regulating cross-border market activity. However, domestic agencies vary considerably in terms of the rate by which these soft law measures are adopted, and the ways in which they spread across jurisdictions are not well understood. This chapter argues that existing theoretical explanations referring to socialization or power dynamics have a specific network-structural pattern associated to them, and that longitudinal network analysis can be used to test their hypothesized effects. In particular, we study the widespread adoption of the International Organization of Securities Commissions' (IOSCO) Multilateral Memorandum of Understanding (MMoU). Based on a longitudinal dataset (2002-2015) of the inter-agency relationships between securities regulators (n=109), we use Stochastic Actor-Oriented Models (SAOM) to predict the rate at which transnational standards are adopted by domestic agencies. The results indicate that standard adoption is contagious in the network of securities regulators.

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2.1 INTRODUCTION

In recent decades, scholars have noted the emergence and importance of transnational regulatory networks in which domestic regulators directly interact with their foreign counterparts, often outside the scope of direct political supervision (Slaughter 2004; Mathieu 2016). For instance, within the Basel Committee on Banking Supervision (BCBS), regulators negotiate about standards on the minimum capital requirements for banks (Goodhart 2011). Similarly, in the International Competition Network (ICN), domestic competition authorities discuss topics of common interest and formulate collective rules and standards on competition policy (Djelic 2011).

Given the absence of formal enforcement authority at the global level, the soft law measures that these transnational networks produce have become increasingly important in regulating cross-border market activity (Maggetti 2014). However, the adoption of principles of 'best practice', standards, and guidelines is typically voluntary, leading some scholars to question the effectiveness of these networks to attain regulatory convergence (Verdier 2009). In any case, countries and their representing agencies vary considerably in terms of the rate by which these soft law measures are adopted, and the ways in which these measures spread across jurisdictions are not well understood (Bach et al. 2016).

Overall, two main narratives exist about the way in which transnational networks potentially foster regulatory convergence (Raustiala 2002). On the one hand, scholars note the socialization potential of transnational networks, in which peer influences and concerns about status or reputation create pressures for agencies to conform to the norm of adoption (Slaughter 2004; Freyburg 2015). On the other hand, scholars argue that power dynamics are more important: weaker and newer jurisdictions will follow the standards set by more powerful actors (Drezner 2008; Bach & Newman 2010). Although both narratives have accumulated supportive qualitative evidence, it has been hard to differentiate between them empirically. In this chapter we argue that both types of explanations have a specific network-structural pattern associated with them, and that longitudinal network analysis can be used to test the hypothesized effects of these patterns on standard adoption. By doing so, we contribute to the standing literature in several ways.

Firstly, most studies on transnational networks use the network concept metaphorically, i.e., as a way to describe a general sense of horizontal interdependence between actors (Legrand 2015; Freyburg 2015). When theorizing about network effects, this metaphorical usage potentially leads to "too much loose analogizing"

(Isett et al., 2011), in which provided explanations are hard to falsify and become too general to account for the specific patterns by which the harmonization or adoption of regulatory rules and standards occurs. A network-analytical perspective helps us move beyond these general explanations, by providing more specific explanations of the variation in terms of the rate at which regulators from different countries adopt standards over time and the degree to which network relationships make a difference.

Secondly, for scholars that have looked more broadly at processes of diffusion (Simmons & Elkins 2004; Shipan & Volden 2012), we note that these studies vary greatly in the way they conceptualize and measure diffusion mechanisms and the role that network interactions play therein (Maggetti & Gilardi 2016). The network modeling approach of this chapter provides a straightforward way to conceptualize and operationalize such network effects, by linking mechanisms to specific network empirical patterns. In this way it becomes clearer, what role these network interactions are likely to play in patterns of standard adoption, besides domestic factors, such as market size (Lenschow et al. 2005), or sectoral factors, such as general levels of policy interdependence (Van Boetzelaer & Princen 2012).

The empirical data to test our hypotheses are drawn from the, by now, widespread adoption of the International Organization of Securities Commissions' (IOSCO) Multilateral Memorandum of Understanding (MMoU). The MMoU is a "soft law" measure on enforcement cooperation, also standardizing several secrecy and blocking laws (Austin 2012). In terms of network explanations of standard adoption, the MMoU is somewhat of a most-likely case, given that adoption is perhaps not as stringent as other transnational standards in terms of adjustments and likely consequences for domestic markets (e.g. capital requirements, see Howarth & Quaglia 2013). However, as it is a case of widespread adoption, the gathered data *does* allow us to meaningfully analyse variation in such adoption and differentiate the network mechanisms playing a role therein. In that sense, the chosen case provides an important plausibility probe for network explanations of standard adoption, particularly when considering that "soft law" measures like the MMoU are becoming increasingly important in other regulatory sectors as well (see Newman & Zaring 2013; Efrat & Newman 2018).

By gathering longitudinal data on the network relationships between agencies and the time at which the MMoU was adopted, we can test whether patterns of adoption can be attributed to the network relationships agencies maintain, and in what way. To do so, a Stochastic Actor-Oriented Model (SAOM) is used, which analyzes the potential co-evolution of networks (the structure of bilateral agency relationships) and behaviour (standard adoption) (Snijders et al. 2010). SAOM-models explicitly allow for testing hypotheses regarding selection and influence effects while accounting for some of the problematic assumptions on which more traditional analyses of adoption are based. In particular, Event-History approaches typically used in diffusion studies assume networks to be static (see Simmons & Elkins 2004), while in reality ties are formed, dissolved, and maintained over time, creating new network contexts in which decisions regarding standard adoption are made (Greenan 2015). SAOMs allow us to model these network dynamics evolving simultaneously with the diffusion of the standard. This chapter thus also presents an important methodological improvement of the current literature that studies network effects in the context of regulatory diffusion (Bach & Newman 2010).

2.2 RESEARCH CONTEXT

The International Organization of Securities Commissions

Our case is the adoption of the MMoU, a standard on enforcement cooperation formulated by IOSCO. IOSCO is a transnational network in the field of securities regulation (Bach & Newman 2010). In its current form, it serves as a core institutional venue for transnational coordination and collaboration between domestic securities regulators. IOSCO is not subjected to any international treaty and it does not have a formal status in international law. Participation is voluntary for securities regulators and the organization strives for universal membership, as opposed to more exclusive clubs such as the Basel Committee (Lall 2015). It has generally succeeded in doing so, as its ordinary and associate members comprise more than 95% of the world's stock markets (IOSCO 2018).

A long-stated goal of IOSCO has been to "facilitate cooperation to promote high standards of regulation" (IOSCO 2018). Since 2010, it has increasingly taken the role of a global standard setter for securities regulation, explicitly focusing on "developing, implementing and promoting adherence to internationally recognized and consistent standards of regulation" (ibid.). Moreover, IOSCO strives to provide "oversight and enforcement in order to protect investors, maintain fair, efficient and transparent markets, and seeks to address systemic risks" (ibid.). To achieve these goals, IOSCO's operations mainly focus on producing policy documents that identify problems in market-issue areas and providing common solutions to policy problems by identifying a common basis for legal oversight regimes, monitoring mechanisms, and enforcement regimes (Kempthorne 2013).

IOSCO generally lacks formal enforcement tools to achieve its goals, and its budget and core staff remain limited. IOSCO mainly functions as a peak organization by providing an institutional point of contact for securities agencies to arrange their cooperation and collaboration among themselves. This typically occurs through participation in specialized working groups and commissions, the annual conference during which its main policy directions are determined, and specific training programs aimed at capacity-building for regulators in emerging markets. In addition to the multilateral cooperation that occurs under the auspices of IOSCO, collaboration between regulators also occurs bilaterally, either on an informal ad hoc basis or through more formalized agreements on information exchange and enforcement cooperation.

The Multilateral Memorandum of Understanding

Despite the absence of formal authority and enforcement tools, IOSCO has made considerable achievements with regard to the harmonization of regulatory rules and standards (Bach & Newman 2010). Its MMoU helped standardize procedures of (multilateral) information exchange and enforcement cooperation, with 109 signatories (see Figure 2.1). The number of information requests under the agreement has also been considerable (see Figure 2.2), implying that adopting the MMoU represents more than just a signatory. Reports of non-compliance have been relatively rare (IOSCO 2007a).

FIGURE 2.1 *Number of Adopters over Time*

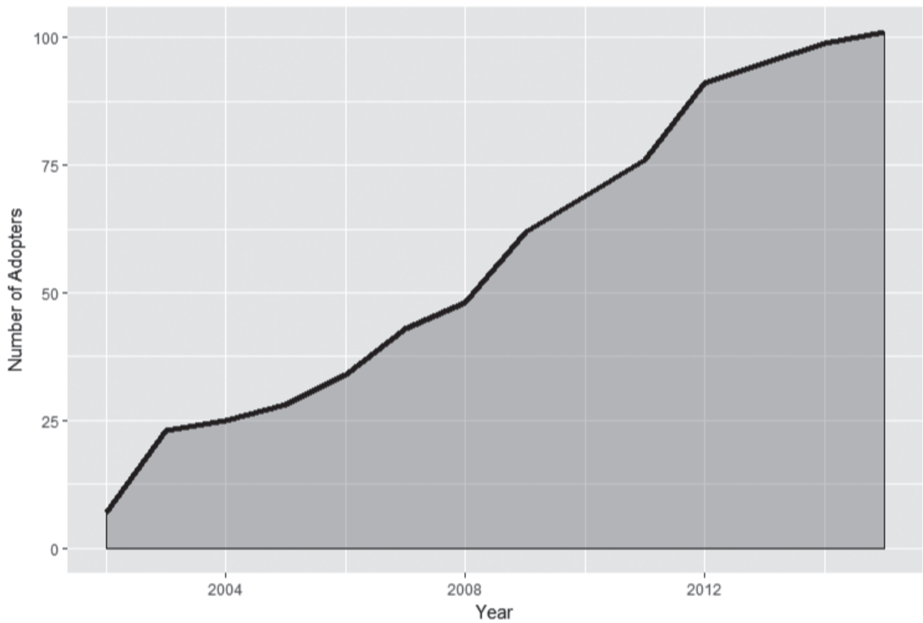
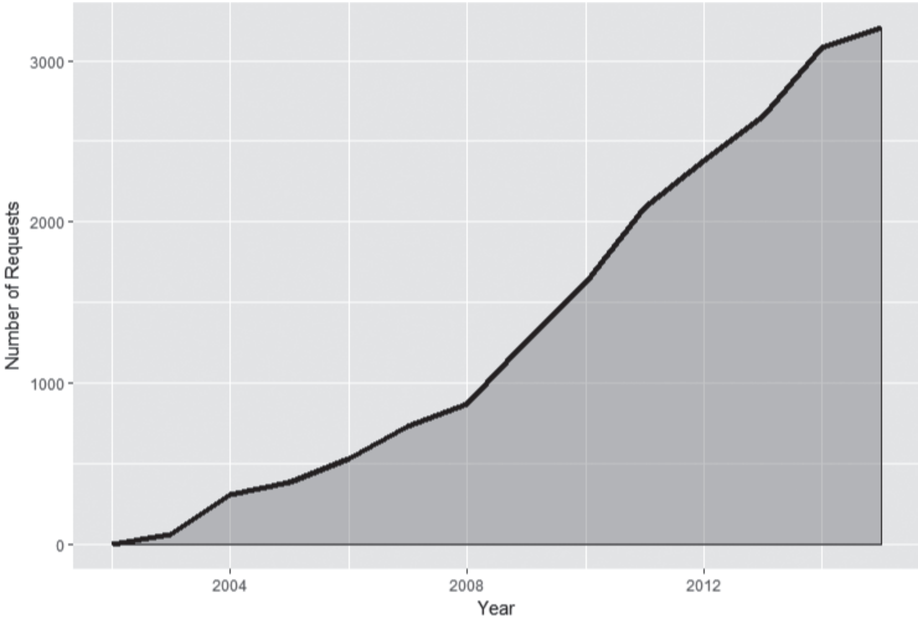


FIGURE 2.2 *Number of Information Requests over Time*



With the MMoU, IOSCO aims to ensure the commitment of domestic regulators to transnational enforcement cooperation and information exchange. In addition to information exchange, the MMoU also facilitates convergence of securities regulation by removing domestic secrecy or blocking laws (IOSCO 2002). Moreover, the MMoU directs that signatories within its framework "provide each other with the fullest assistance permissible to secure compliance [of their respective securities laws and regulations]" (IOSCO 2002). It includes rules concerning the scope of assistance required, the procedures to be followed, permissible uses of the information provided, confidentiality, and the limited circumstances under which assistance may be denied (Austin 2012).

Figure 2.1 shows that, over time, the MMoU has been widely adopted by its members. A general explanation for this pattern is easily provided. For instance, the MMoU may have proven to be a convenient technical solution for the problem of enforcing domestic regulatory rules and the prosecution of cross-border financial crimes. Economic network effects and tipping points may increase the MMoU's usefulness as more regulators sign the agreement over time (Raustiala 2002). Alternatively, events such as the financial crisis may have pressured regulators to commit to cross-border collaborative arrangements.

However, such explanations fail to account for the *sequence* and *rate* of MMoU adoption over time. In other words, why did Portugal's securities agency adopt this standard in 2002, and the Argentinians in 2014? Agencies may initially lack the willingness or capacity to adopt the MMoU but eventually decide to do so. Adopting the MMoU thus requires a significant behavioural change on behalf of the agency. Below, we argue how network relationships influence this behavioural change and how such explanations account for the variation in the rate at which different regulators adopt the MMoU.

2.3 THEORETICAL FRAMEWORK

In the standing literature on transnational regulatory networks we observe that "network effects" are often ascribed importance (Raustiala 2002; Legrand 2015). In particular, scholars have underlined the potential influence of these networks on processes of regulatory convergence, in which networks act as channels of diffusion for the spread of transnational standards (Maggetti & Gilardi 2011; 2014). However, the way in which these networks have an effect has been the subject of much debate. Two main narratives exist regarding the role of transnational networks and their importance for understanding the spread of standards such as the MMoU .

The first type of explanation emphasizes *socialization*. Advocates of this approach describe the process of harmonization as a decentralized, incremental process of interaction and emulation in which networks play an important role (Slaughter 2004). Through socialization and peer influences, networks promote norms that contribute to the effective implementation of international standards (Maggetti & Gilardi 2011). Particularly because networks bring together regulators on a repeated basis, they may come to "define their roles partly in relation to their transnational reference group rather than in purely national terms" (Keohane & Nye, 1974: 45). For the adoption of soft rules, preferences and identities of actors engaged in transnational networks can thus be mutually transformed through their interactions with each other (Finnemore & Sikkink 1998). This type of explanation can be linked to established diffusion mechanisms, such as emulation and (social) learning (Gilardi 2012).

A second type of explanation emphasizes the *power dynamics* involved in transnational forms of networked interaction. According to this perspective, powerful actors can use transnational networks to promote policy export and shape foreign legislative agendas (Bach & Newman 2010). Concentrated regulatory power fosters convergence, as weaker and newer jurisdictions ascribe to the norms and standards set by more powerful actors (Drezner 2008). In promoting the global export of their domestic policies, lead regulators backed by significant market power may use (information) asymmetries within the network to their advantage. Rather than horizontal collaboration, powerful agencies seek to control networks and their decision-making as to secure favorable distributional outcomes, at the expense of weaker jurisdictions. Such explanations are closely linked to the diffusion mechanism of *coercion* (Gilardi 2012).

The standing literature has had difficulty to differentiate between these types of explanation through empirical analysis. We argue that this primarily has to do with a metaphorical usage of the network term, in which networks represent a particular form of collaboration or organization characterized by horizontal relationships and informal interaction (Slaughter 2004). Although this provides a useful way to characterize a sense of horizontal interdependence between actors and to differentiate them from more hierarchical forms of organizing and interaction, such a conceptualization is not very clear on the precise network properties that are assumed to drive diffusion.

An alternative to treating networks as metaphors is by contextualizing network properties with reference to formal social network analysis (SNA) (Christopoulos 2008). Through SNA, we can give abstract concepts related to networked forms of collaboration, such as social capital, trust, and density, a more precise theoretical formulation. The way to do so is by perceiving networks as sets of relations that form patterns or regularities (i.e. a network structure). This allows one to examine structural variation in networks and assess its effects on actors and outcomes (see Wasserman & Faust 1994). Instead of studying network effects by only looking at network membership as an agency attribute (cf. Bach & Newman 2010), such an approach does more justice to the reality that activity, contacts, and structural embeddedness can vary greatly between and within member agencies over time. To do so, we must ask how structural variation is related to socialization and power dynamics (cf. Maggetti & Gilardi 2011).

Network-Structural Hypotheses

To formulate hypotheses, we have to specify socialization and power dynamics in network-analytical terms. For this, it is useful to distinguish between two dominant streams of network research, which differ in the way in which they treat network ties and their functions: a *connectionist* and a *structuralist* perspective (see Borgatti & Foster 2003).

First, a *connectionist* (or relational) perspective assumes networks to be channels that facilitate the flow of relational resources, such as information, experience, or support (see Lin 2001). These resources are transmitted through interaction between network actors and variation in (behavioural) outcomes can thus be explained on the basis of the differential exposure or access of actors to these resources. Following such a reasoning, network relationship play an important role in explaining standard adoption patterns on the basis the diffusion mechanisms of (social) learning and emulation in particular (see Burt 1987).

Regarding (social) learning, when domestic agencies seek information on the potential implications of adoption, they typically draw on the experiences of their *direct* network partners, whose actions and opinions are most salient and influential. Through interaction, network partners develop a shared understanding of the costs and benefits of adoption. If many direct network partners of a focal agency have already adopted a standard, it is likely that this understanding primarily favors the benefits of adoption, and thus increases the likelihood of adoption for the focal agency. Moreover, in the case of an agency lacking the capacity to adopt, network relationships can provide the necessary knowledge and resources to help build the capacity to fulfill the conditions set by IOSCO for signing the MMoU.

Regarding emulation, network relationships have also been shown to play an important role (Finnemore & Sikkink 1998). The adoption decision may be driven by concerns about reputation, status, or legitimacy. Being connected with many agencies that have adopted a standard potentially creates pressures for agencies to conform to the norm of adoption set by its network partners or direct reference group. Concerns about reputational losses from non-adoption, for instance, may lead to the adoption of standards, even if there is uncertainty about the potential outcomes or effectiveness of the standard for the focal agency.

A logical inference from the connectionist perspective is that agencies that have many network relationships to others that have already adopted the standard, will likely also adopt the standard themselves. We thus expect that an agency's likelihood of adoption increases proportional to the number of adoptees within the agency's ego-network. Therefore, regarding the adoption of the MMoU, we hypothesize that:

H1: The larger the proportion of other agencies (alters) that have a direct network relationship with a focal agency (ego) and have adopted the MMoU at time point t*, the more likely the focal agency (ego) is to adopt the MMoU at* t+1.

Second, a *structuralist* (or positional) perspective focuses on the structure and configuration of the network as a whole, looking at broader patterns of network embeddedness (see Burt 1987). This perspective assumes that actors within a network can make use of their structurally advantageous position in the network, which is usually defined by some measure of centrality. Centrality typically refers to the number of ties that actors maintain with the network, and actors with high centrality are assumed to be able to easily access resources and information due to their ties with many other actors. These central actors are therefore able shape the flow of information between other actors and influence the adoption decisions of others to align with their own preference.

Central actors that have adopted the MMoU are likely to become *advocates* of its further spread and enforcement, as an increased number of signatories effectively extends the usefulness of the MMoU for their own enforcement purposes (Raustiala 2002; Bach & Newman 2010). They may do so by blocking the flow of unfavorable information, encouraging the spread of favorable information, taking credit for the (timely) sharing of critical information, or threatening to negatively portray an agency to (a larger group of) other agencies in the network. Such reasoning can thus be linked to the diffusion mechanism of coercion, which states that powerful agencies can pressure others into adopting policies or standards.

From this perspective, we can explain variation in adoption by looking at the differential connections of agencies to those with structurally advantageous positions in the network. A structuralist perspective predicts that central actors exploit power asymmetries in order to impose their policy preferences on "weaker" agencies. Specifically, agencies most sensitive to such advocacy or coercion are likely to be those to which they are most closely connected through direct network relationships. Being connected to such central actors that have adopted the MMoU thus increases the probability that an agency will likewise adopt:

H2: The higher the centrality of other agencies (alters) that have adopted the MMoU and to which a focal agency (ego) has a direct network relationship at time point t*, the more likely it is that the focal agency (ego) will adopt at* t+1.

Potential Confounders

Regulatory agencies (and the jurisdictions they represent) vary considerably on a number of dimensions – e.g., power, size, budget, staff, political-institutional context – that all likely influence both the network relationships that they maintain *and* the rate at which they adopt regulatory standards (Bach & Newman 2014). Therefore, we discuss several potential confounders that we control for in the empirical analysis.

First, we note the importance of market size in transnational financial regulation. The "weight" of an agency, represented by the importance of their jurisdiction and size of the market they regulate, likely impacts their popularity with other actors (i.e., more direct relationships) and their stakes regarding regulatory convergence (i.e., MMoU adoption) (Drezner 2008). Second, an agency's degree of regulatory independence "back home" is important to consider, as this is an explicit condition (provision) for adopting the MMoU and makes it easier for agencies to engage in bilateral network relationships with each other (Bach & Newman 2014). Third, the activities of actors within IOSCO should not be discounted. The more active agencies are in IOSCOs various working groups and commissions, the more likely it is that they will form network relationships with foreign counterparts and become advocates of IOSCO standards and initiatives (Bach & Newman 2010). Lastly, we should control for network activity in general (a focal agency's number of direct relationships), as both the formation of network relationships and the adoption of standards may signal an agency's functional need toward transnational collaboration, for instance because of having a more internationalized market.

In addition to agency characteristics, we also consider three relational characteristics of "pairs" of agencies. First, the geographical proximity of actors in relation to each other likely affects both the tendency of agencies to engage in network relationships and their likelihood to adopt regulatory standards in response to each other (see Cao 2012). Second, in addition to IOSCO, there are several regional platforms of securities regulators, such as ESMA, COSRA, and ACMF. Given that membership in these platforms increases the chances for agencies to engage in network relationships, it also increases the chances that collective decisions on adopting global standards are made (Quaglia 2014). Third, agencies that share important political-institutional characteristics, such as established autonomous and independent government agencies (Jordana et al. 2011), will likely have lower barriers to cooperation and some of these characteristics may be favorable to the conditions of adopting the MMoU.

2.4 METHODOLOGY

Data Collection and Operationalization

To build our dataset, we first registered the precise dates at which different regulators adopted the MMoU. At the time of data collection (2016), IOSCO's MMoU had

109 signatories, of which 104 constitute our sample[5]. We determined the years when each of these 109 agencies became a full signatory of the MMoU. This information was coded over time (2002-2015) in panel format, changing the agencies' value from '0' to '1' in the year they signed the MMoU.

To reconstruct the network of bilateral relationships between these 104 regulators, we collected longitudinal data on the formation of bilateral Memoranda of Understanding (MoU). Bilateral MoUs typically reflect well-established channels of communication, potentially transmitting information and resources (Brummer 2011). Such bilateral agreements are typically formed between agencies that interact more frequently to limit the transaction costs of constantly specifying conditions of co-operation and making agreements on the nature and confidentiality of exchanged information (see Slaughter 2004). In particular, the negotiation of bilateral MoUs requires intensive interaction between regulatory agencies and gives us the guarantee that at least some form of contact or interaction exists, or has existed between the regulatory agencies that establish such an agreement. When compared to other measures of networked interaction, such as network membership in general (Bach & Newman 2010) or co-membership in commission or working groups (Maggetti & Gilardi 2011), for which systematic and reoccurring contact is not guaranteed, bilateral MoUs serve as a more valid operationalization of direct network relationships. Comparability between agencies and availability of data over time are two other critical considerations.

Still, choosing bilateral MoUs as our main measure for network relationships may seem counterintuitive, particularly when using these relationships to explain the adoption rates of a *Multilateral* MoU. Both kinds of agreements appear to serve similar purposes and the observation that agencies maintain a large number of bilateral MoUs and are quick to adopt the MMoU may simply signal functional necessity or cross-border information exchange rather than real influence. However, in terms of commitments and requirements for regulators, the MMoU greatly exceeds those of bilateral MoUs (Brummer 2011). Moreover, if the signing of both bilateral MoUs and

5 During the data collection process, five signatories were dropped from the analysis for two reasons. First, Central African and Western African countries signed the MMoU as a regional platform, meaning that data derived from these countries tell us little about the adoption decision and network behaviour of individual national regulators. Second, two countries - Japan and the USA - had multiple actors reported as signatories to the MMoU. Given the size and importance of these countries – and its likeliness of skewing our analysis, particularly in terms of the control variables - we dropped two Japanese ministries and the US CFTC and chose the main securities regulator of both countries as the primary actor. The final sample for our analysis thus comprised 104 regulators over 14 time waves.

the MMoU are driven by the same factors, this should show up in our models where we control for this potential confounding tendency. In particular, by including the general tendency of agencies to form bilateral ties and assessing whether it has an effect on the rate of adoption, such problems of endogeneity can be dealt with.

Given that no dataset of bilateral agreements was available, we coded the relationships between securities agencies for the period 2002-2015. To do so, we first consulted the "international cooperation" sections typically maintained on the securities' regulators websites. Second, we cross-checked this information with evidence from annual reports and press releases to reconstruct the dates of initiation of bilateral agreements. Third, for the agreements that were only reported by one side, we examined the signed agreement to validate the relationship. To be conservative, we discarded relationships that were only reported one-sidedly and for which an official document or other documentation could not be obtained. We coded the resulting information into adjacency matrices (one for each year) in which the existence of a relationship between agencies was denoted by a '1' and a '0' otherwise.

Control Variables
At the actor level, we gathered data on *market size* from the World Bank and IMF to determine countries' GDP over time (2002-2015). To measure *regulatory independence*, we determined the legislative acts through which regulators were declared independent and subtracted the year of the legislative act from 2015 (cf. Jordana et al. 2011). This left us with a quantitative indicator that serves as a proxy for the independence of an agency. To capture *institutional activity* within IOSCO, we obtained working group and commission membership data of agencies within IOSCO from their website and coded the number of working groups in which agencies participate. To account for the potential stakes that agencies might have in the MMoU, we coded agencies that were part of IOSCO's *Technical Committee* at the time of MMoU initiation, which was the platform's primary decision-making body at the time.

To measure *geographical proximity*, we subdivided agencies based on the country regions identified in the QoG dataset (Teorell et al. 2018). For data on regional platforms, we examined existing institutional platforms in the field of securities regulation and constructed an affiliation matrix based on membership information. Due to strong overlap with geographical proximity, we only coded EU regulators separately, given that they participate in the most institutionalized form of regional cooperation, namely CESR/ESMA (Howell 2017). Lastly, to capture the political-institutional context of countries, we extended the dataset of Bianculli et al. (2013) on the different *administrative traditions* of countries. For countries that were not reported in this dataset, we primarily used the QoG dataset (Teorell et al. 2018) and Painter and Peters (2010) for further categorization.

Analytical Strategy

We test the hypotheses using a Stochastic Actor-Oriented Model (Snijders et al. 2010). These models have been developed to describe and explain the co-evolution of network and behavioural characteristics over time. Given the nature of our data and the process of diffusion in which we are interested, we use a SAOM-extension so that the adoption times follow a proportional hazard model (Greenan 2015). An in-depth discussion of the model assumptions and estimation procedures is beyond the scope of the present study (see Ripley et al. 2018 for an in-depth discussion). Here, we present a non-technical discussion to aid in understanding the results of the estimated models and argue for the appropriateness of the approach given our research question and hypotheses.

The Appropriateness of SAOMs to Study Standard Adoption

Our primary reason for using a SAOM is that we want to take into account the way in which networks evolve simultaneously with the diffusion of standards. Standard diffusion studies that rely on Event History Models typically assume the network to be static, and model the time to an event as depending on a set of exogenous factors. However, modeling adoption and network evolution as a joint process allows us to incorporate explanatory variables which account for the dependencies that the network and the adoption of standards have on each other over time (Greenan 2015). This is a much more realistic representation of how network influences work in transnational diffusion processes.

Moreover, the standard cross-sectional (and longitudinal) regression-based models that are typically used to estimate contagion and diffusion effects in international politics also have several problematic limitations (Snijders & Pickup 2018). First, these techniques assume independence between observations and thus cannot account for the inherent interdependence between actors in complete networks. Second, network studies are typically unable to separate processes of network evolution (*selection)* and behavioural change (*influence)* and cannot control for potential alternative mechanisms that drive these processes (Steglich et al. 2010). Overlooking these problematic and interrelated issues when estimating the effects of networks on behaviour (or vice versa) likely leads to biased results and invalid inferences.

Estimation Procedure and Assumptions

The basic idea of a SAOM is that it defines the totality of possible network (and behavioural) configurations for a given set of actors as a state space of a stochastic process and models the observed network dynamics by specifying parametric models for the transition probabilities between these states. When working with panel data, each measurement (panel wave) of the network corresponds to one state in the overall state space, and we explain network dynamics by examining the transition probabilities by which the network "jumps" from one observation to the next. The first observation is conditioned upon and is taken as the exogenously given starting value of the stochastic process. The choice to create ties is modelled simultaneously with the choice to adopt (hence the co-evolution of networks and behaviour), and both decisions depend on previous states of the network and adoption at *t-1*.[6]

For our behavioural dependent variable, the only transition we empirically observe in the network of securities regulators is from '0' to '1', representing that the actor adopts the standard. This observation is characteristic of the diffusion of innovations in networks: once an agency has adopted a standard, it is stuck with it. Therefore, we include our predictor variables in the so-called *behavioural rate function* to model the *time to an event* (i.e., adopting the MMoU). A proportional odds time-to-event model is integrated with a SAOM of network dynamics, as described by Greenan (2015). The rate function aims to reflect the observed MMoU adoption process, as shown in Figure 2.1.[7]

6 Because the set of possible transitions between states is potentially very large, some simplifying assumptions are necessary. First, it is assumed that the transitions between panel measurements are manifestations of an underlying process (of network and behavioural evolution) taking place in continuous time. Second, actors are assumed to act conditionally independent of each other and only make decisions given the current state of the network. Third, actors change at most one tie or behavioural variable at a time. Observed transitions are then modeled by decomposing them into network- and behavioural 'mini-steps'. A rate function indicates the speed at which the network actors have an opportunity to make such changes, and the objective function indicates how these changes actually appear, e.g., effects capturing tendencies toward triadic closure (Ripley et al., 2018).

7 Given the distinctive features of our network data, several additional issues must be addressed. First, we observe a network in which ties (bilateral MoUs) were never terminated between agencies. Therefore, in our model, the actors only have the option to create new ties or retain the status quo and cannot delete existing ties (cf. Ripley et al. 2018: 25). Second, given that we study a non-directed network (i.e., consisting of ties in which both actors have a say in its formation), we must consider how ties are created between two agencies. We assume network relationships are created by means of 'unilateral initiative and reciprocal confirmation' (Snijders and Pickup 2018). 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 must confirm, otherwise the tie is not created (Ripley et al. 2018: 50). Given that MoUs must be signed and agreed upon by both agencies, this process best captures how bilateral agreements between national agencies are formed in practice.

Modeling the Hypothesized Network Effects
To test the first hypothesis, we included an *average exposure* effect (Ripley et al. 2018: 173). This effect captures the tendency for actors to become similar to their alters. It is defined as the proportion of an agency's alters who have adopted the standard, assuming that the higher this proportion is at *t*, the more likely an agency is to adopt at *t+1*. A positive average exposure effect indicates that the adoption of the MMoU at time t follows from the proportion of the agency's alters that had adopted the MMoU at *t-1*.

For the second hypothesis, we included an *infection-by-degree* effect (ibid.). This effect is defined as the sum of the degree of an agency's alters: if a network partner that has many connections in the network adopts the standard, this likely has a larger influence on your own likelihood to adopt compared to an alter that adopts but is peripheral in the network. Rather than merely looking at adoption behaviour of network partners, this effect thus takes into account the "power" of those partners, as defined by their degree centrality (i.e. the number of ties that an actor has).

We also included a *degree effect* (ibid.: 172) to assess whether the tendency to have ties increases the rate at which standards are adopted. This effect disregards whether the agency's network partners have adopted the MMoU and simply focuses on the network activity of the agency (ego) itself. A positive parameter value indicates that the more network relationships an agency maintains at time *t,* the higher the likelihood that the agency will adopt the MMoU at time *t+1*.

In addition to these effects on the *rate of adoption*, we also include effects that capture how the *formation of bilateral agreements* evolves over time. This helps us separate selection and influence effects by assessing whether the status of standard adoption also affects an agency's partner choice at *t+1*. Finally, we also included general effects that capture basic network dynamics, such as the overall network tendency toward triadic closure (see Ripley et al. 2018: 41-42). For the control variables *working group participation, administrative traditions and geographical proximity*, we added (dyadic) similarity effects to assess whether agencies that share traits on these indicators are more likely to form network relationships. A summary of all effects are given in Table 2.1 and 2.2.

TABLE 2.1 *Summary of Included Effects (Y=MMoU Adoption)*

Name of Effect	Description of Effect	Data Source Control Vars.
Average Exposure (H1)	Captures whether the proportion of *i*'s alters that adopt the MMoU predicts *i*'s rate of adoption	
Infection by Degree (H2)	Captures whether the centrality of *i*'s alters that have adopted the MMoU predicts *i*'s rate of adoption	
Degree Effect	Outrate: captures whether the number of network relationships *i* maintains, predicts its rate of adoption	
Market Size	GDP (scaled): captures whether *i*'s market size (measured in GDP) predicts its rate of adoption	World Bank, IMF
Regulatory Independence	Captures whether *i*'s independence (measured in years since establishment act) predicts its rate of adoption	i.a. Jordana et al. 2011
Institutional Activity	Captures whether the number of IOSCO working groups in which *i* participates predicts its rate of adoption	IOSCO Website
EU-Member	Captures whether CESR/ESMA (EU agencies) membership predicts *i*'s rate of adoption	ESMA Website
Technical Committee	Captures whether membership in IOSCO's technical committee memberships predicts *i*'s rate of adoption	IOSCO Annual Rep.

TABLE 2.2. *Summary of Included Effects (Y=Network Formation)*

Name of Effect	Description of Effect	Data Source Control Vars.
Triadic Closure	Captures tendency toward triadic closure for undirected networks.	
Indirect Ties	Captures the tendency for agencies to keep indirect ties (number of actor pairs at distance 2)	
Shared WG	Captures whether agencies that participate in the same IOSCO working groups are more likely to form ties	IOSCO Website
Geographical Proximity	Shared Region: whether agencies that are located in the same region are more likely to form ties.	QoG dataset
Shared Adm. Tradition	Captures whether agencies that share the same administrative tradition are more likely to form ties	i.a. Bianculli et al. 2013
Adoption Alter	Captures the tendency of a relationship to form if the alter has adopted the MMoU	
Adoption Similarity	Captures the tendency of a relationship to form between agencies if both have adopted the MMoU	

Estimation Strategy

We use the SIENA package in R to estimate our SAOMs. The estimation procedure aims to achieve a convergent model, meaning that the expected value comes sufficiently close to the target or observed values. However, particularly for networks with many nodes (n>100) and time waves (>3), estimation becomes highly complex and convergence can be difficult to achieve. To manage these issues, we made two choices in our modeling procedure. First, rather than immediately estimating a complicated model with many effects included, we gradually constructed our model by beginning with our base effects. After this simpler model converged satisfactorily, we continued to add effects, taking the previous estimates of our simple model as the starting values for the more complicated model (see Ripley et al. 2018: 63). For some effects, estimating the precise numerical values of parameters was problematic and led to convergence problems. As a solution, we 'fixed' these effects at zero (meaning that these parameters are not allowed to vary) and conducted score-type tests for significance (see Schweinberger 2012).[8] The parameter and standard error values of these effects are represented as 'fixed' and '.000' in Table 2.4, respectively. For effects that could not be included in the model due to convergence problems, the parameters are labelled 'NA'.

Second, we subdivided our full period of 14 years into three shorter periods. This is partly a modeling choice, as shorter periods reduce time-heterogeneity, which causes parameter values to shift too heavily over time, creating convergence problems (Lospinoso et al. 2011). It also helps account for important exogenous events that are relevant for our research context. To determine the cut-off points, we have no strong a priori expectations; the only event that stands out in our research context was the start of the global financial crisis in 2007. We took that year as the first cut-off point and subdivided the remaining eight years (2007-2015) into two periods of equal length. This resulted in three time periods for analysis (2002-2007; 2007-2011; 2011-2015), for which we assume the contexts to be relatively constant.

2.5 RESULTS

Figure 2.3 provides a visual representation of our network data. The nodes represent regulatory agencies and the ties between them represent the existence of a bilateral MoU. Based on how this network evolves over time, we want to assess whether the

8 Sometimes the inclusion of too many weak effects can lead to severe convergence problems. SIENA may have trouble determining precise numerical values for these parameters. From a modeling perspective, a straightforward solution is to exclude these effects. However, including these effects may be important on theoretical grounds. Following Ripley et al. (2018: 65), we fix these effects at zero, meaning that their parameter values do not vary during simulation. They can be included in the model but do not interfere with the estimation process (of the other parameters). Moreover, through score-type tests, these 'fixed' parameters can be tested for significance (see Schweinberger 2012).

pattern of adoption follows from the network relationships that agencies maintain. Visualizations for four years are shown (2002, 2007, 2011, and 2015). Note that the black nodes signify non-adoption.

FIGURE 2.3 *Network Visualizations*

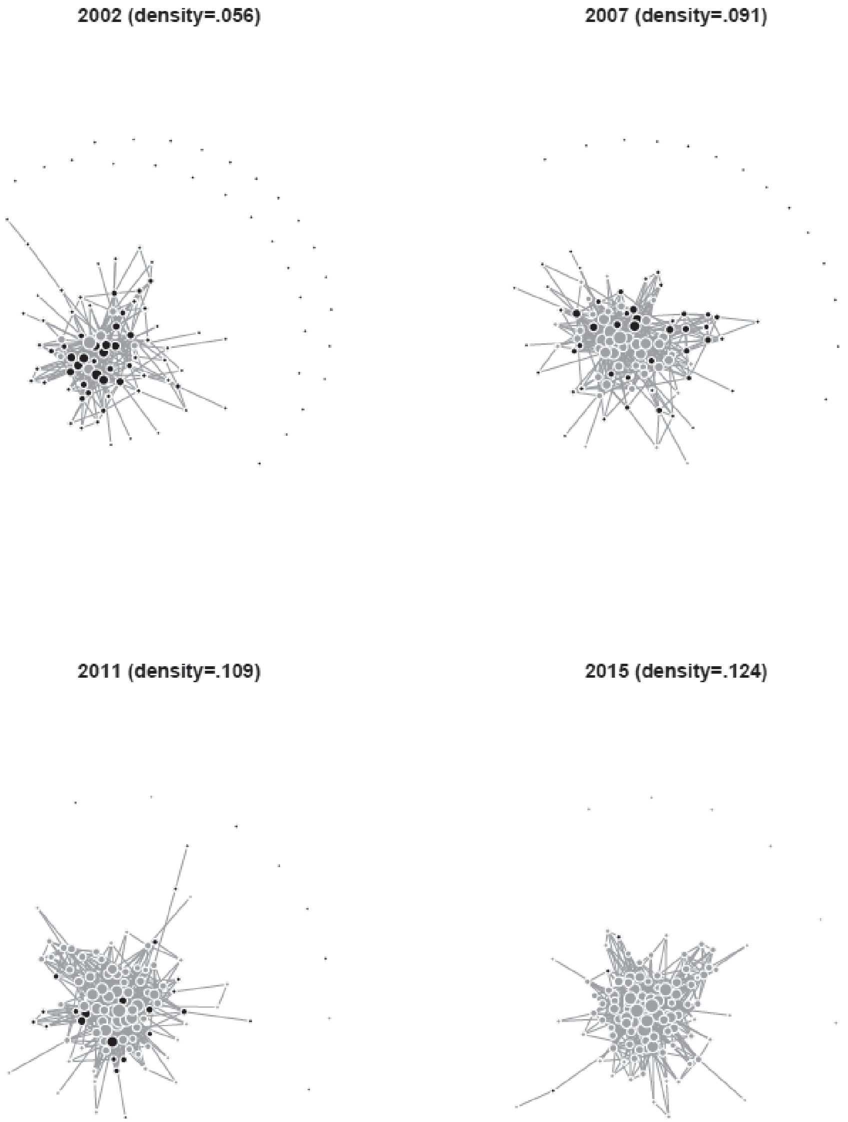


TABLE 2.3 *Network Descriptive Statistics 2002-2015*

Observation Time	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Density	.056	.062	.068	.077	.083	.091	.096	.101	.106	.109	.114	.118	.121	.124
Average Degree	5.77	6.37	6.98	7.92	8.56	9.33	9.89	10.39	10.89	11.21	11.71	12.12	12.48	12.75
Number of Ties	300	331	363	412	445	485	514	540	566	583	609	630	649	663
Jaccard-Index	NA	.906	.912	.881	.926	.918	.944	.952	.954	.971	.957	.967	.971	.979
MMoU Adoption (%)	6.7	22.1	24.0	26.9	32.7	41.3	46,2	59,6	66,3	73,1	87,5	91,3	95,2	97,1
Number of Adoptions	7	16	2	3	6	9	5	14	7	7	15	4	4	2
Cumulative Adoptions	7	23	25	28	34	43	48	62	69	76	91	95	99	101

Table 2.3 provides the descriptive statistics of our main variables, and shows that the number of adoptions increase steadily over time. The density of the network describes the number of ties in the whole network as a proportion of the possible number of ties given the number of actors. Given that we only observe the formation - never dissolution - of bilateral relationships, the network becomes increasingly dense over time.

SAOM Results

The results of our explanatory analyses are presented in Table 2.4. Regarding the hypotheses of interest, we observe that in the first period of observation (2002-2007), the *average exposure* parameter has a significant positive value, meaning that there is a tendency for agencies to adopt the MMoU when a large proportion of their network partners have adopted the MMoU (*b*=2.117; *S.E.*=0.954). Although the interpretation of parameters in SAOMs is not straightforward, they can approximately be interpreted as a log-odds-ratio of an increase in behaviour compared to remaining constant (Ripley et al. 2018: 168). For our model, which follows a proportional hazards model (Greenan, 2015), this odds-ratio describes the hazard of adopting the MMoU. If an agency's average exposure increases by $\delta \in [0, 1]$, then their hazard (of adoption) increases by approximately 8.5^{δ} (because $\exp(2.117) \approx 8.3$; cf. Greenan 2015: 160)[9]. General activity (*degree effect*) or infection-by-degree do not affect the rate of MMoU adoption.

For the network dynamics effects, there is a tendency toward triadic closure in our network. This means that agencies that are connected to the same agency through a bilateral MoU at point *t* tend to form a bilateral MoU with each other at *t+1*. In addition, once an alter has adopted the MMoU, it typically decreases the likelihood that a bilateral relationship will be formed with that agency (*adoption alter*). The same holds when both agencies have adopted the MMoU (*adoption similarity*). Both parameter estimates are significant in our model, which is intuitive given that the MMoU could be argued to replace the function of bilateral MoUs, i.e., it only makes sense for agencies to form additional bilateral agreements if they exceed the conditions set by the MMoU. Lastly, agencies that are geographically proximate (*shared region*), participate in the same working groups within IOSCO (*shared WG*), or share the same administrative traditions (*shared AT*) have a higher chance of forming bilateral relationships, with all estimated parameters significant at the 0.01 level.

9 This means that, if the proportion of an agency's alters that have adopted the MMoU increases by 0.3, this makes an agency approximately twice as likely to adopt the MMoU than when this proportion remains the same (because $8.5^{0,3} = 1.9$).

TABLE 2.4. *Results Table*

	Period 1		Period 2		Period 3	
	(2002-2007)		(2007-2011)		(2011-2015)	
Variables	*Estimate*	*SE*	*Estimate*	*SE*	*Estimate*	*SE*
Network Dynamics						
Triadic Closure	.395*	(.068)	.512*	(.112)	.314*	(.122)
Indirect Ties	-.032	(.027)	.021	(.036)	-.030	(.052)
Shared WG	.306	(.109)	.058	(.237)	.000	(fixed)
Geographical Proximity	.478	(.246)	.243	(.385)	.841	(.490)
Shared Adm. Tradition	.923	(.236)	.545	(.383)	.601	(.421)
Adoption Alter	-.889*	(.338)	-.525	(.441)	NA	NA
Adoption Similarity	-1.259*	(.305)	-.324	(.459)	NA	NA
Behavioural Dynamics						
Degree Effect	.126	(.084)	.321	(.244)	.274*	(.062)
Average Exposure (H1)	2.117*	(.954)	3.328*	(1.292)	-1.402	(.841)
Infection by Degree (H2)	-.005	(.007)	-.022	(.014)	.000	(fixed)
Regulatory Independence	.010	(.011)	.007	(.015)	-.008	(.028)
EU-Member	.724	(.486)	-.182	(.900)	.000	(fixed)
Technical Committee	.576	(.764)	.961	(2.581)	.000	(fixed)
Institutional Activity	.085	(.108)	.319	(.247)	-.833*	(.310)
Market Size (GDP)	-.522	(.571)	.000	(fixed)	NA	NA

Notes: All convergence t-ratio's < .06. Overall maximum convergence ratio .16

In our analysis of the second period (2007-2011), many estimated parameters no longer significantly affected our network and behavioural dependent variables of interest. However, regarding hypothesis 1, we observed an increase in the parameter estimate of our average exposure effect (b=3.328 *S.E.*=1.292), which is also significant at the 0.01 level. This means that for an average exposure increase of δ, the hazard of adoption increases by approximately 28^{δ}. Regarding the other two hypotheses, both general activity (*degree effect*) and infection by degree did not affect the rate at which regulators adopt the MMoU.

In the third period (2011-2015), the average exposure effect is no longer significant and does not appear to affect adoption rates. However, the degree effect capturing network activity is significant. This means that, in this last period, agencies that maintain many network relationships at point t are more likely to adopt the MMoU at $t+1$ (b=.274 *S.E.*=.062). Institutional activity, captured by the number of IOSCO working groups in which an agency participates, had a strong negative effect on adoption rates. This may be because many institutionally active IOSCO members adopted the MMoU early on. Regarding network dynamics, the last period also showed a strong tendency toward triadic closure.

Interpreting MMoU Adoption Dynamics

Overall, we conclude that the early stages of adoption of the MMoU reflect a slow start. The MMoU was initiated during the aftermath of 9/11, when there were concerns regarding the use of financial markets for terrorist financing (IOSCO 2002; Austin 2012). However, the initial response to the MMoU was meagre, with only 25 adopters after the first two years. A 2007 IOSCO report assessed the obstacles to adopting the MMoU for regulators of "emerging markets". Although they saw the need for international collaboration and a majority was favorable to the initiative, regulators had difficulty preparing their applications and meeting the requirements (IOSCO 2007b). Moreover, regulators also reported that they did not see a need for the MMoU because they were satisfied with existing forms of transnational collaboration or had little transnational activity to regulate (ibid.). Given the positive exposure effect found in this first analysis period, the limited number of additional agencies that adopted the MMoU before the crisis were primarily persuaded or pressured into the MMoU by their network peers.

The period from 2007 onwards proved to be the start of more turbulent times for securities regulators. Stock markets fell heavily and distorted the global economy into a financial crisis. This heightened the urgency of cross-border collaboration, which is reflected in the higher number of adoptions in this period. IOSCO itself may have played an important role in this upsurge of adoptees, given that they threatened to make IOSCO membership conditional upon signing the MMOU (as of 2010). Despite this, many of these new adoptions follow the patterns of the agencies' network relationships, given the relatively high value of the average exposure parameter. The strong exposure effect in this period is potentially explained by the uncertain context of the global financial crisis and subsequent need for action on behalf of regulators.

By requiring all members to become signatories by 2010, IOSCO also became more active in pursuing a higher rate of adoption (IOSCO 2008). However, regulators still reported struggling with the requirements of the MMoU, particularly in terms of obtaining necessary legislative authority and sharing investigative results with foreign counterparts (IOSCO 2008). In 2012, further conditionalities were formulated regarding adoption of the MMoU (IOSCO 2014). With the creation of a watch-list for non-signatories as of 2013, IOSCO used a strategy of shaming regulators into adopting the MMoU (IOSCO 2013a). Moreover, IOSCO further limited the opportunities of non-signatories to influence decision-making with the so-called *Graduated Additional Measures*, which gradually stripped non-adopters of leadership positions, committee participation and voting rights over the course of 2014 (IOSCO 2013b).

The effectiveness of "review panels" that exert peer pressures for compliance has also proven effective in similar kinds of transnational regulatory networks (Maggetti & Gilardi 2014). Through the use of such instruments, IOSCO's secretary thus played a more important role in persuading non-signatories to adopt the MMoU. This potentially explains the absence of endogenous network effects in the final period of analysis, as other (exogenous) factors become more important. However, it seems plausible that such institutionalized measures only work once a significant number of countries has already adopted or backed a standard or guideline (cf. Mukherjee & Singer 2010).

2.6 DISCUSSION AND CONCLUSION

In this chapter, we used a network-analytical perspective to study how transnational regulatory standards and principles spread across jurisdictions. Given the increasing importance of these "soft law" measures in regulatory practice, understanding the patterns by which they are adopted is crucial (Newman & Zaring 2013). Although scholars frequently point to the importance of network effects in studying processes of regulatory harmonization (Raustiala 2002; Bach & Newman 2010), theoretical intuitions are rarely explicated by rigorous empirical analysis. In this chapter, we accounted for the variation in the rate at which securities agencies adopt an enforcement cooperation standard, namely the MMoU, and were able to distinguish between different mechanisms that drive this process.

Specifically, our results indicate that the rate of adoption is driven by the adoption behaviour of direct network partners (hypothesis 1) and peer influences thus play an important role. However, the network positions of agencies (hypothesis 2) in terms of the centrality of their alters does not make a difference. Overall, these findings clearly favor a *connectionist* perspective on the effects of network relationships in processes of regulatory harmonization and the domestic adoption of standards, emphasizing mechanisms of emulation and learning, rather than a *structuralist* perspective emphasizing power dynamics and the mechanism of coercion (cf. Maggetti & Gilardi 2011).

These findings have several implications. Firstly, at the theoretical level, this chapter justifies the inclusion of network-structural variables when modeling decision-making regarding standard adoption and specifies in what way they are likely to have an effect. In particular, a more precise conceptualization of network-structural variables provides a better understanding of *how* transnational relationships can function as channels through which standards spread, and gives theoretical guidance on how structural variation across networks is likely to affect patterns of standard adoption. Next to domestic factors, such as regulatory independence (Bach & Newman 2014), or sectoral factors, such as levels of regulatory interdependence (Van Boetzelaer & Princen 2012), the embeddedness of agencies in transnational patterns of communication with other agencies is crucial to consider.

Secondly, the analysis clarifies the role that network relationships can play in transnational regulation, at different stages of development. In the absence of formal authority and enforcement tools at the global level, networks can help to orchestrate dispersed actors toward a common solution or collective action (Kenis & Schneider 1991). Particularly in the first stages of standard adoption, in which much uncertainty exists about the necessity and consequences of particular standards, such relationships drive adoption behaviour and can thus be utilized to steer collective outcomes. In later stages, more institutionalized and concrete forms of steering by network coordinators become more important. These insights are particularly valuable for understanding the way in which network structure plays a role in the potential of transgovernmental networks to act as regulatory intermediaries (see Jordana 2017). In particular, in facilitating regulatory activities and disseminating soft law standards, the relational structures that exist within networks are likely to moderate the effects that these intermediaries have.

Thirdly, the analysis offers a methodological contribution, as it demonstrates the importance of longitudinal designs and statistical network models in understanding processes of regulatory harmonization. In terms of making causal arguments regarding the effects of network relationships, such analyses allow for establishing temporal order between the formation of network relationships and adoption behaviour (see Snijders & Pickup 2018). Moreover, statistical network models such as SAOMs allow for modelling network changes, rather than assuming networks to be static.

Regarding the generalizability of our results, we concede that our argument may be limited to the specific type of standard we examined –, i.e., a multilateral agreement on information exchange and enforcement cooperation, standardizing blocking and secrecy laws across jurisdictions – or only holds for the specific domain of securities. However, the coordination and collaboration dilemmas described in the context of the MMoU are not particular to securities regulators. The need for cross-national information exchange and enforcement cooperation is typical for many regulatory sectors (see Efrat & Newman 2018), and we can reasonably expect the network dynamics found in our analysis to also be present in other (regulatory) research contexts.

In conclusion, transnational networks do not operate in a vacuum: powerful environmental, political, and historical forces also affect the behaviour and decisions of regulatory agencies. Network dynamics are thus one of many factors to consider and they depend on the presence and quality of such contextual conditions as well. However, the key message of this chapter is that, if we want to take transnational network influences seriously, we should map the specific relations of the network itself and systematically assess how they are related to overall outcomes and the behaviour of agencies. Rather than treating networks as black boxes and assuming they have an effect of some sort, the specific relationships that agencies maintain and the local structures in which they are embedded are likely to significantly shape the rate and sequence of diffusion processes in transnational regulation.